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Fruit Type Recognition Using Hybrid Method with Principal Component Analysis (PCA)

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ABSTRACT
This research concentrated on fruit image recognition. Fruit recognition in this study can be used to estimate the number of fruits that exist. Data testing is used to classify a fruit image that has been trained to recognize a variety of labels (fruit types). Until the classification process, several processes and methods are used in this research, one of which is the Gaussian filter to improve the quality of fruit image recognition. In addition, the Gabor filter is used in the feature extraction process, and the PCA technique is used in feature selection to select the best features. To classify the chosen feature, deep learning and the k-nearest neighbor (k-NN) method will be used. Furthermore, the processes used improved the accuracy of 92%, a root mean squared error (RMSE) of 0.323, a mean squared error (MSE) of 0.6278.

Keywords: *Deep learning, K-nearest neighbor (k-NN), Gaussian filter, Principal component analysis.*

1. INTRODUCTION

The detection of this type of fruit is frequently regarded as critical because the object detected is a human requirement in life. In order to detect the type of fruit, the system must be able to recognize it accurately. Many academics propose deep learning-based fruit recognition techniques to address the issue of fruit detection accuracy [1]. Fruit recognition can assist fruit vendors in identifying and distinguishing various fruit varieties that share some characteristics [2]. This is consistent with the findings of Jun Lu and Nong Sang[3], who used robot media to detect citrus fruits. As with fruit detection, using an RGB camera as a detector of choice (due to its convenience and ease of implementation) involves detecting fruit.

Using an RGB camera as a detector of choice (for its practicality and ease of implementation) involves detecting fruit characteristics such as color, shape, and texture[4]. Fruit detection is frequently performed by a group of researchers with the goal of assisting in recognizing the faction or type of fruit without having to think ahead of time if the person does not have much knowledge about the type of fruit. Because of inconsistency and inaccuracy, a significant portion of the bug identification process is still done manually, adding time and expense [5]. Object introduction research is mostly done in the field of medicine to detect the type of human disease. Fruit is a healthy food in general. As a result, fruit type recognition in this research is required for researchers as a contribution to the treasury of science and to assist most men in fruit type recognition.

Image processing technology is now widely used in a variety of fields. Image-processing technology is used in the field of commerce to read barcodes on goods in supermarkets. Image processing is also used in medicine, such as NMR (Nuclear Magnetic Resonance), robotic fruit recognition [3], and ultrasound image reconstruction.

Digital images are classified into two types: silence images (a single image that is not moving) and moving images (a series of silence images displayed in a row, giving the impression of movement). A frame is the name given to each image in the circuit.

A discrete (not continuous) digital image can be described as a matrix, where the row and column indexes of the matrix represent the position of a point in the digital image and the price of the matrix element represents the color of the image at that point. According to Ryszard S. Choras [5,] a digital image can also be expressed as a two-dimensional function f (x, y), where x or y are coordinate positions and f is the amplitude at position (x, y), which is commonly referred to as intensity or grayscale.

According to a study conducted by M. Omid et al [6], According to M. Omid et al [6], a digital image is an image expressed in a digital data set that can be processed by a computer. A variety of digital devices are used to acquire digital imagery. According to D.M. Bulanon et al [7], a cloud image is obtained using a digital camera, an image of a newspaper article is obtained using a scanner, an image of a signature is obtained using a light pen, and cells are obtained using a microscope.

The research scope of a recognition is specifically for fruits in this study. It is consistent with the findings of Hulin Kuang et al [8]. The goal of fruit recognition is to provide detailed information about the fruit as well as to recommend fruit to people. The quantization process is also required in the above-mentioned conversion. Each pixel's gray level is represented by an integer price in this process. The integer price limit or gray level area size used to denote the pixel gray level, which determines the brightness resolution of the obtained image. If the integer price is stored in three bits, it can have up to eight levels of gray. The greater the number of gray levels used, the better the image will be obtained because the gray level continuity will be greater, resulting in a closer match to the original image.

1.1. Conversion of Analog Images

The digital image is a two-dimensional array or matrix whose elements express the image's gray level. Images play an important role in machine learning techniques as well as applications such as feature extraction, object recognition, and object categorization [9]. As a result, the information contained is discrete, but the digital image is not always a direct result of a system's recording data. Data recordings are sometimes continuous, such as images on television monitors, photos, rays, and so on. To obtain a digital image, a conversion process was required, so that the image could then be processed by a computer [6]. To convert a continuous image into a digital image, the process of making horizontal and vertical direction clues is required, resulting in an image in the form of a two-dimensional array. The procedure is known as digitization or sampling. The array is known as a picture or pixel element in these elements. The spatial resolution obtained by dividing an image into pixels by the size of this point is determined, which means that the smaller the pixel size, the smoother the image obtained because the information lost by gray level clustering on the lattice grid making process is smaller.

We use image filtering techniques such as the Gaussian filter for preprocessing and the Gabor filter for feature extraction in this study. Then, to select features, we use principal component analysis (PCA). The matrix will be generated as part of the feature selection process and will be used as input in the classification process, which will employ deep learning and k-NN algorithms. As a result, in this study, we use the image as input and the classification process's accuracy to determine the type of fruit to the dataset that we use.

According to R.M. Alonso-Salces et al [10], who investigate species recognition based on fruit maturity. Fruit varieties are classified by determining ripe and raw fruit. In their research, they use a multivariate approach [10], which can accommodate some of the image dataset's features. The multilayer feed-forward artificial neural network (MLF-ANN) was used as a classification method. The study's results with a ratio of 97 to 99% are classified as "mature" and "raw" on the final label.

J. Blasco et al [11] investigated fruit type detection and stated the importance of early detection of fruit fragments such as rotting, wilting, and others in order to avoid contagious on other fruits. The data used in their study [11] is multispectral data. While morphological features are available as a determinant component for the classification process. This feature is used to clarify the image during fruit density recognition or detection. The approach to or recognition of fruit types is primarily determined by the visual characteristics of the fruit and the methods used in distinguishing fruit types from other objects using image processing techniques; however, the use of this method can be influenced by environmental factors such as complex backgrounds, variable light, overlapping, and occlusion with other plants, making accurate fruit recognition difficult[12].

Jyoti Jhawar [13] detects fruit maturation as well, using the Edited Multi-Seed Nearest Neighbor (EMSNN) technique and the Linear Regression technique to classify fruit maturity. A system built using the linear regression technique can recognize fruit maturity with an accuracy of 90 to 98% and can group fruit that has never been labeled before. The developed system is working on the color and texture recognition of recognizable fruit for recognition classification and unrecognized fruit for clustering. Peng Wan et al [14] conducted another study that detected tomato maturity by using computer vision as a medium to detect tomato maturity. It is related to machine vision-assisted harvesting [7]. The machine vision implementation study [14] was carried out in a laboratory, also known as in vivo research. The tomato was the object studied, and the detection system was focused on the color of the tomato fruit. Back-propagation neural network (BPNN) method was also used to identify tomato maturity.

2. METHODS

To achieve the best results in recognizing the type of fruit, we used a system described in this study in the form of images, as shown in Figure 1. In our study, there are two processes. The first step is to convert the image's input into a matrix. The use of images has a goal: to create a classifier capable of identifying a much broader range of fruits [15]. The Gaussian and Gabor filters are used in the image-to-matrix conversion process. According to Mohammad Haghighat et al [16], this Gabor technique is in terms of the tested image's invariance of scale, rotation, and translation. Mohammad Haghighat et al [16] also stated that this technique can reduce the amount of noise in the process of classification or other image processing determinations, which can be difficult with photometric. The filter result is then used to select one of the many features of the selection technique, but the technique used in this study is principal component analysis (PCA). The process of feature selection results in a matrix-shaped image representation. The image matrix is then input into the classification process, which uses deep learning and k-nearest neighbor (k-NN) algorithms, based on the resulting matrix. The matrix image as an input is classified by their respective region in this classification process. This classification process is repeated because the matrix classification method employs deep learning in image processing. To determine the type of fruit in this study, we compartmentalized the fruits used in the training dataset based on the region present on the fruit.

In our study, we used a dataset that contained 260 public raw datasets of fruit images that had not been preprocessed, extracted, and selected the features, all of which were downloaded from https://www.kaggle.com/moltean/fruits/data. The validation process makes use of the available data, which is spread across two (2) labels. This dataset has been scaled down so that computing with a 10x10-pixel size does not take too long. The label's two (2) Pear and Strawberry.

The computation time for the classification phase to perform the experiment ranges from twelve (12) seconds when these personal computer specifications are used. We use the C # application for the first process, which is the input image to the preprocessing process, followed by the feature extraction process. We used a Rapid miner Studio application tool up until the feature selection phase, i.e. principal component analysis (PCA). This is done to incorporate the results of these processes into the matrix. Then it moves on to the classification phase, where deep learning and k-nearest neighbor (k-NN) algorithms are used to achieve the expected classification results.

To identify the type of fruit, several techniques and methods that can be considered a grip are required to achieve the desired results. The following are some of the techniques and methods we used in this study.

2.1. Pre-Processing

The Gaussian filter is used to remove noise from the process before classification, which enhances the image. According to Ryszard S. Choras' research [17], filtering is a part of the preprocessing stage, and the results of this stage are the picture region and object. This is required for the following step.

2.2. Feature Extraction

It is possible to identify an image's pattern by dissecting its many components into their unique properties with the use of feature extraction. A feature that has evolved will be used to classify data from training and testing sets. In this work, we used the Gabor filtering technique.

2.3. Feature Extraction

According to Ryszard S. Choras' research [17], feature selection is used to identify patterns and eliminate features that are not important for the classification phase but have a substantial impact on the classification process. The goal of this feature selection is to speed up the classification process and achieve high accuracy. In this study, we employ principal component analysis, one of the picture segmentation approaches (PCA). It is crucial to properly segment images in order to obtain the appropriate accuracy level during the segmentation process.

2.4. Classification

The fruit picture recognition process makes use of classification. In this study, the k-nearest neighbor (k-NN) and deep neural network techniques were utilized for classification. In this study, we also use the Bag-Of-Words (BoW) feature representation as the input from 2,000 initial features, all of which have not been preprocessed using methods against it. Instead, we extract the features using the Gabor filter feature extraction and principal component analysis (PCA) feature selection. After entering all the features, a forward propagation procedure was conducted out using the features. From the input layer, move in phases to the hidden layer, then the output layer. We calculate the error using the result from the result in the hidden layer.

To calculate the error rate that happens between the inputted feature, each layer being compiled, and the output layer generated, we execute the calculation using the error function from the result in the hidden layer. The backward propagation algorithm is used to achieve the smallest error until the convergence of the feature value is discovered after the usage of the error function and the result of the error achieved. While the k-nearest neighbor (k-NN) technique was also used to calculate similar results.

The weighting method is carried out in this instance to provide a strain on each weight in addition to the deep learning idea, which is generally combined with a mixture of numerous hidden layers. The epoch will obtain the desired value from the updated weight by applying the weight. In comparison to earlier techniques, deep learning is better at detecting objects [18].

We also employ the hyperbolic tangent activation function (TanH) in this study, which is incorporated in our hidden layer and, according to[19], can simplify the model constructed to interact with the dataset used, which is primarily documents or text. Furthermore, we employ the softmax activation function for the activation function that is implemented in the output layer. One might claim that using this activation function makes it easier to build models that efficiently assemble data and is associated with offering a stronger gradient than the activated sigmoid function.

We use as many as eight (8) dimensions of classes feature image inputs in the form of features for the design we apply to the application of deep learning and k-nearest neighbor (k-NN) for the classifying of the fruit recognition, which is the results of feature selection process using principal component analysis (PCA) technique. In this study, we used two (2) final labels including various types of fruits.

3. RESULTS AND DISCUSSION

In this study, we convert an image to a matrix, which is then used as input for the classification process. As a result, we used a measurement of results to measure the effectiveness of all processes to the expected result, which Abinash Tripathy et al [20] stated in their research is widely applied to the process of text classification. In fact, in this study, our result is in the form of text with the obtained accuracy; however, the input is in the form of an image. In the process of determining the outcomes of all processes, from dataset preprocessing to classification using deep neural networks and k-nearest neighbor (k-NN) algorithms.

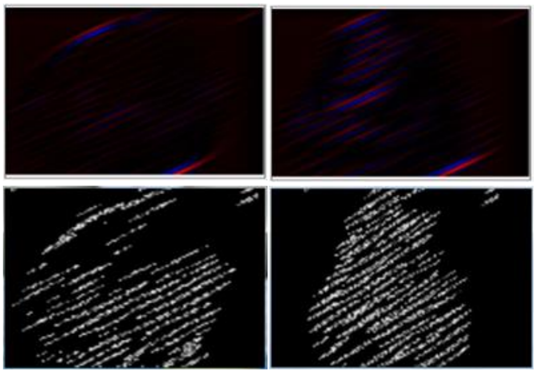

Figure 1 The output of the extraction procedure using the Gabor filter.

The accuracy achieved by our implementation of several processes, including preprocessing, feature extraction, feature selection, and classification method usage until prediction, is 92%. Using the Gaussian filter for feature extraction, the Gabor filter for feature selection, and Deep Neural Network and k-Nearest Neighbor (k-NN) as hybrid classifiers, we were able to recognize the fruit types based on our dataset. To help people understand the outcome of the discussion, graphs and tables with values of kappa, root mean squared error (RMSE), mean squared error (MSE), and accuracy were presented.

Table 1. Result

Table 1 displays the accuracy, RMSE, and MSE values obtained from the classification phase using Deep Neural Network (DNN) and k-nearest neighbor (k-NN) classifiers and obtained using the Gaussian filter for preprocessing, Gabor filter for feature extraction, and principal component analysis (PCA) for feature selection.

4. CONCLUSION

Based on our study with some of the processes and methodologies, we can infer that using deep learning and k-nearest neighbor (k- NN) classification methods can decrease the excessive mistakes in the fruit recognition process. With an accuracy of 92%, a root mean squared error (RMSE) of 0.323, a mean squared error (MSE) of 0.6278, and other filtering techniques, the image can be improved.

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