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Fruit recognition Using Statistical and Features Extraction by PCA

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ABSTRACT

A diet high in fruit can help us avoid diseases such as cancer, diabetes, heart disease, and others. Without professional dietitian guidance, a method that quickly reveals how many calories in fruits they are consuming can be helpful in maintaining health. Image processing methods is used to expanding across all academic fields, including food science and agriculture. The identification of plant fruits and the extraction of their features are covered the first topics in this essay because they are essential to agriculture. The main goal is to use the results of Principal Component Analysis (PCA) to build an accurate, efficient, and reliable framework. Fruit detecting software could simplify human labor. Based on color and shape characteristics, several fruit recognition methods have been developed. However, the color and shape values of many kinds of fruit photos could be comparable or even the same. As a result, utilizing PCA features extraction analysis methods to identify and distinguish fruit photos is still workweek and effective enough to boost recognition accuracy. In this paper, a fruit recognition algorithm based on PCA is proposed. The database that has been used in this study contains six distinct categories and 36 fruit images. Despite the fact that this approach used PCA for feature extraction to implement the system in this research paper, the proposed system's classification accuracy is reached around to 75%.

KEY WORDS: Fruit, recognition, Feature extraction, Fruit Classification, Principal Component Analysis (PCA).

1. Introduction

Calories, vitamins, fiber, phytochemicals, and minerals are abundant in fruits. They are a crucial component of the human diet. Fruits have a lot of potassium, fiber, and vitamin C, but they don't have much fat, sodium, or calories. A diet high in fruit can help us avoid diseases including cancer, diabetes, heart disease, and others. The Centers for Disease Control and Prevention state that eating fruit has benefits for your health and can help you control your weight [1]. The majority of vegetables have fewer calories when compared to other foods. As a result, regularly consuming this fruit can aid in weight loss or health management. One of the most rapidly expanding fields in computer science is image processing. Nowadays, analog imaging is being replaced by a digital system as a result of technological advancements. Large-scale image acquisition occurs every day, and maintaining these photos manually over time is quite challenging. As a result, the idea and use of digital imaging are expanding quickly. Different attributes can be extracted from photos using digital image processing [2]. Systems for object detection, matching, extracting, and analysis heavily rely on feature extraction techniques. Additionally, it compares different techniques. This paper [3] suggests a novel cucumber region detection technique employing a multi-path convolutional neural network (MPCNN), color component selection, and support vector machines in order to increase the practicality and accuracy of the automatic recognition models (SVM). In this technique, the cucumber picture was converted into color space to produce 15 color components, and I-RELIEF was used to analyze the weight data of important characteristics. This paper introduced a novel cucumber region detection technique employing a multi-path convolutional neural network (MPCNN), color component selection, and support vector machines in order to increase the practicality and accuracy of the automatic recognition models (SVM). In this technique, the cucumber picture was converted into color space to produce 15 color components, and I-RELIEF was used to analyze the weight data of important characteristics. Furthermore, Principal Component Analysis (PCA), the most popular technique in the study of odor recognition, frequently fails to identify the crucial features required to complete recognition tasks [4]. The E-nose system's recognition accuracy is typically decreased as a result. This research suggested a unique odor recognition approach for the E-nose system based on the initial sensor response and the ReliefF algorithm, and applied it to identify and categorize three types of fresh and rotten fruits (apple, pitaya, and tribute -citrus). The findings demonstrated that the odor recognition time can be significantly decreased by merely extracting information from the initial stages of sensor response. ReliefF can choose the critical characteristics more effectively than the conventional PCA approach, which increases the E-nose system's identification accuracy. By utilizing textural cues and examining various illumination intensity distributions on citrus and background objects, [5] proposed a novel method to identify immature citrus. Although the detection accuracy is not affected by strong natural light, the detection efficiency is excellent in low light conditions. Results from training two models on three datasets based on the same training data but with distinct feature extraction methods are presented in this [6] article. The purpose of this project is to compare the outcomes of various model and feature combinations in order to better comprehend these methodologies and strategies. The models used for classification are support vector machines (SVM) and random forests (RF). Principal Component Analysis (PCA), bespoke features based on color and shape, and finally the Discrete Fourier Transform (DFT) combined with PCA are examples of feature extraction techniques. They suggest a method for fruit recognition and calorie estimation in this publication [7]. For the purpose of fruit recognition, they have presented an approach that involves segmenting precise images utilizing k-mean clustering, color fragmentation, texturing tools, and a few other elements of the cloud SVM process. They trained a data set, including calorie tables for each fruit label, in order to estimate calories. For the purpose of fruit recognition, they have presented an approach that involves segmenting precise images utilizing k-mean clustering, color fragmentation, texturing tools, and a few other elements of the cloud SVM process. They trained a data set, including calorie tables for each fruit label, in order to estimate calories. They have provided a method for segmenting exact images for the purpose of fruit recognition using k-mean clustering, color fragmentation, texturing tools, and a few other aspects of the cloud SVM process. To estimate calories, they trained a data set that included calorie tables for each fruit label. It is capable of precisely detecting the fruit with precision, usually exceeding the rate of 80%. The actual positive examples are quite frequent, which is a benefit. On the other hand, a drawback is that it is difficult to estimate calories accurately since they rely on the size and weight of the fruits. The datasets in this case are fairly rigid. High performance systems are needed for CNN models, and more executable time is needed for guiding the signal. The network that is proposed [8] uses a visual sensor to do real-time identification and semantic segmentation of apples and branches in orchard situations. The proposed detection and segmentation network makes use of the gate feature pyramid network and arouse spatial pyramid pooling to improve the network's ability to extract features. A lightweight backbone network built on the residual network architecture is created to enhance the network model's real-time calculation performance. The structure of this paper is as follows: In section 2, "Related Work," Section 3 describes the background theory, and Section 4 provides the proposed system. Section 5 discusses the results and the discussion. This paper ends with a conclusion in Section 6.

2. Related Work

In [20], to reduce the number of features, PCA was used. The threshold was set at 95% variance. A preprocessed fruit image has 79 features in total that were taken from it. An innovative fruit categorization method known as HPA-SLFN was provided in this study. The findings indicated that HPA-SLFN had a classification accuracy of 89.5%, which was higher than that of other approaches. (PCA) performs a change of basis and computes the principal components of a set of data. Sometimes it only uses a handful of them while ignoring the remainder. In statistical analysis, linear combinations are discovered using linear discriminant analysis (LDA). Because they both search for linear combinations, it is the same as PCA. In order to classify the optical ripeness of Cape gooseberries, five multivariate knowledge fusion methodologies were used: LDA, PCA, IDA, multi-cluster characteristic selection, and Eigen-vector center characteristics selection. Fruit samples are distinguished using a variety of color spaces by classifiers like NT, SVM, and KNN. A few classifiers can perform better because the color spaces are equivalent up to a transformation and changes in the distribution of sample pixels. They achieved the highest accuracy in [21] by using the 7-dimensional PCA feature space. For instance, a methodology to analyze several pairings of machine learning methods with color spaces (RGB, HSV, and L*a*b*) was put forth in [22] to assess their suitability for categorizing Cape gooseberry fruits. The outcomes demonstrated that the ripeness level classification of Cape gooseberry fruits was sensitive to both the color space and the classification method applied. Regardless of the color space, the models based on the support vector machine (SVM) classifier and the L*a*b* color space performed the best. Principal component analysis (PCA) was used to combine the three-color spaces, which resulted in an improvement at the cost of added complexity. The project suggested in [23] aims to classify 18 different types of fruits using feature extraction, reduction, and SVM. For better outcomes, a mix of color, the GLCM texture feature, and form measurements are applied. When compared to other efforts that have been stated in the literature, the experiment's results of 87.06% significant classification accuracy are encouraging. The PCA feature vector is reduced and contains the whole set of retrieved features. Latent variables are produced using PCA, a technique for dimensionality reduction, from linear combinations of the original data in [24]. Principal components (PCs), also known as latent variables, are ordered, orthogonal to one another, and greedy in such a way that early PCs capture more variability than later PCs. A (64 by 128 pixel) image with 8192 dimensions can be reduced to a reduced-dimensional representation defined by a predetermined number of independent PCs using PCA. Many of the dimensions are correlated with one another (for example, nearby pixels). As a result, PCA can be used to impose independence across variables while also reducing dimensionality. Citrus huanglongbing was first identified by [25]. Following boundary advancement, the sound and HLB-tainted samples were compared to models of several AI measures, such as the SVM, k-nearest neighbor (KNN), logistic regression (LR), naive Bayes, and ensemble learning. All models had the most specific and intelligible PCA characteristics when paired with distinctive CNs (computerized numbers), it was discovered. The maturation level of FFB is divided into three categories in this work [26]: raw, ripe, and half-ripe. The suggested approach utilized the color and texture features necessary for feature selection and classification. Principal component analysis (PCA) was used to pick the most significant characteristics after applying the feature extraction procedure based on color and texture. The prediction class was then obtained by applying an ANN with a back-propagation algorithm to the classification process.

2.2 Technique Comparison

This section discusses and displays Table 1 of several studies based on fruits' PCA properties.

Table 1: comparison between the researches based on PCA feature extraction method.

Aim of study	Dataset	Accuracy	Ref.
Classification	online collecting using Google	89.5%	[20]
Classification	925 samples of Cape gooseberry fruits were collected from a plantation located in the village of El Faro	--------	[21]
Classification	925 Cape gooseberry fruit samples	89.8%,94.2%,93.02%	[22]
Classification	655 images from different datasets	87.06%	[23]
Detection	8192-dimensional image	----------	[24]
Detection-Classification	Use commercial multispectral camera (ADClite) mounted on DJI M100 UAV (unmanned Aerial Vehicle) in a field	97%	[25]
Selection – classification	local dataset consisting of 240 images	98.3%	[26]

3. Background Theory

This section describes the developed fruit recognition system, as well as the technique, algorithm, and data used to create it.3.1 Feature extraction The technique of gathering more detailed information about significant objects in a picture is known as feature extraction [9]. A classification technique that overfits the training samples and performs badly when applied to fresh samples is typically needed for analysis with a large number of variables. A way of creating combinations of the variables to get past these issues while still accurately describing the data is known as feature extraction [10][18]. In pattern recognition, features frequently include information about context, shape, texture, or grayscale. In image processing or machine vision, a pattern measurement from the beginning or certain successive measurement patterns are transformed into a new pattern feature [11]. The process of classifying an object into a category or a class using the extracted features or higher-level data from the object is known as "pattern classification." By creating the classification method, it also automatically recognizes items in the image [12]. Computer science's significant topic of pattern recognition is concerned with identifying patterns, especially visual and auditory patterns. It employs strategies from the fields of statistics, machine learning, and others. [9]. 3.2 PCA algorithm as is all aware, compression and recognition issues can be resolved using the dimensionality reduction method known as Principal Component Analysis (PCA). Eigenspace projection or hoteling are other names for PCA [13]. By using Principal Component Analysis (PCA), the original data space or image is transformed into a subspace collection of Principal Components (PCs), where the first orthogonal dimension captures the majority of the variation between the images. Based on the statistical properties of the targets [14], the last dimension of this subspace shows the least amount of difference between the images. The mean square error can be the minimum when characterizing the original vector using the orthogonal or uncorrelated output components from this transformation. Popular transform methods like PCA produce results that aren't specifically tied to any one feature component of the original sample. PCA's ability to extract features lets it find the parts of sample data that change the most. This can be used to pick out a few interesting people from all the profiles. The PCA approach typically discovers a projection matrix Wopt that maximizes the determinant of the total scatter matrix of the projected samples [15] as follows: Where ***w*** is: ,W-opt.=,arg-,max-w., |,w-T.,s-T.w |-, |w-T.,s-w.w |.. (1) and ST is the total scatter matrixes: ST=,1=1-c-,,,x-i.−μ)(,x-i.−μ.-T.. (2) The notation μ represents the mean feature vector of all samples in the training set, xi is the i-th sample's feature vector, and c is the total number of the training samples.

3.3 Confusion Matrix

One idea behind machine learning is the confusion matrix, which has information about how things were actually categorized and how they were thought to be categorized by one of the classification systems. The confusion matrix is a matrix of two dimensions; the rows are known as the actual classes, while the columns are known as the prediction classes. As shown in Figure 1, the basic form of the confusion matrix for a binary classification task is the classes, where TP (true positive) is the outcome where the model correctly predicts the positive class. While the TN (true negative) is an outcome where the model correctly predicts the negative class, the FP (false positive) is an outcome where the model incorrectly predicts the negative class. But the false negative (FN) is the outcome of the model that incorrectly predicts the positive class. Figure 1. Confusion Matrix Finding the proportion of correctly categorized samples to the total number of samples is necessary to determine the accuracy of the classification models, as illustrated in the example below. $Accuracy$=,TP+TN-TP+TN+FN+FP. ………. (3) To find the precision for the TP divided by the total number of the elements labeled as positive (the sum of the TP and FP) as shown in formula 2. When the precision is high, that means the model and the classification are producing more relevant results. $Precision$ =,TP-TP+FP. ……….. (4) To find the sensitivity of the model, one needs to calculate the recall by dividing the total number of elements that actually belong to the positive class TP, as shown in formula 3. $Recall$ ($sensitivity$) =,TP-TP+FN. The proposed system 5 suggested method, which performs feature extraction using PCA, is presented in this section. Principal component analysis's (PCA's) main goal is to minimize the number of interconnected variables in a data set while preserving as much of the data set's inherent volatility as possible. The PCA has been discussed in detail in Section II. Principal Component Analysis techniques are divided into two stages: training and recognition [15]. For more details about the proposed system, see the block diagram in Figure 2. It illustrates the steps of the proposed system. Figure 2. System Diagram Training Step: The approach used in this phase is to extract the eigenspace from the training image, which was previously transformed into a data matrix. An Eigen matrix is built from data samples that the system must be able to identify, and it turns the samples into points in eigenspace. The image samples are converted to grayscale. transformed into a 1D column vector from a 2D matrix (N2 x 1). To create the data matrix (picture set) X of N2 x n dimensions, arrange the column vectors of n photos. Compute the mean vector of the data vectors in matrix X. By removing the mean vector, normalize the data matrix X's vector. Calculate the column vectors' covariance matrix as in (2). Compute the eigenvalues and corresponding eigenvectors using (3): The eigenvectors of the covariance matrix should be found in order to reach the dimensionality reduction [16]. The set of eigenvectors associated with the eigenvalues. The eigenvectors should be arranged from high to low in accordance with the associated eigenvalues. This matrix of eigenvectors is called eigenspace. The set of eigenvectors associated with the eigenvalues Set the eigenvectors' order from high to low based on the matching eigenvalues. This matrix of eigenvectors is called eigenspace. The data set's highest eigenvalues for main components correspond to the vectors with the greatest variance [17]. w=eig,,S-T.. (6) Get the P by projecting the data matrix X onto the eigenspace. P=WTX (7) Recognition Step: This step involves getting the eigenspace from the test image, which was earlier transformed into a data matrix. To determine the minimum difference, these results were compared to those from the training period. The recognized image should be converted into an ID vector and subtracted using the mean. focusing on the same eigenspace Calculate the Euclidean distance between each projected sample in P and the image that was recognized: The most analogous image is represented by the smallest Euclidean distance value. The flowchart about the suggested system and the training and testing procedures is shown in Figure 3 below. 5. Results and Discussion Figure 3. Flowchart of the Proposed System The experiments that were run to test the suggested strategy are described in detail in this section. For the evaluation, the Fruits-360 dataset [19] was used, and the approach software used MATLAB platform.

5.1 Data set

All of the images for training and testing were selected from the Fruits 360 dataset, which is available to the general public on Kaggle. The dataset [19] includes 90380 pictures of 131 different fruits and vegetables. The fruits were registered while being rotated by a motor, which subsequently produced frames to capture the images of the fruits. As a backdrop, white paper was positioned behind the fruits. A flood-fill method was used to separate the fruit from the backdrop due to the uneven illumination. All the fruits were scaled to 100x100 pixels of typical RGB photos after the background was removed (therefore, 3 values for each pixel). The training dataset has 67,692 photos, whereas the test dataset contains 22,688 images. [19]. From the fruits360 dataset, 42 pictures from different categories were selected. 36 of the acquired fruit photographs were used to design and train the system, while another 6 fruit images were used to test the system. These fruit images have been divided into training fruit set and testing fruit set.

5.2 Result

The training fruit images must be sent in and processed using PCA before analyzing the model using the confusion chart to determine precision and recall, as shown in figure 4.

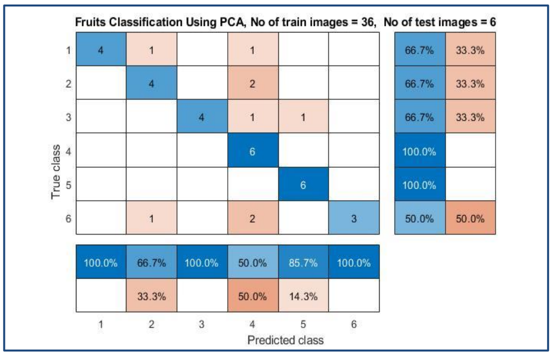
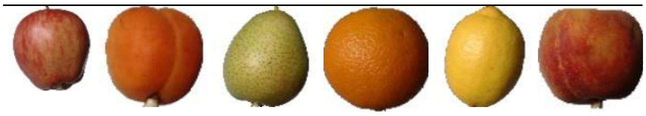


Figure 4: Confusion Matrix

In this system's database, there are 6 classes for (Apple, Apricot, Pear, Orange, Lemon, and Peach), as shown in Table 2. For each class, there are 6 images.

Table 2: Tests class

Apple	Apricot	Pear	Orange	Lemon	Peach
1	2	3	4	5	6



From the confusion chart, the table in the middle of the confusion matrix shows that the orange's recall is 50%, which is lower than other fruits, but the highest rates are found for the apple, pear, and peach, which reached 100%. On the other hand, as shown in the right table of the confusion matrix display, the precision rate among the orange and lemon is a high percentage of 100%. However, the peach is about 50%. As shown in the confusion matrix, it illustrates that for the peach there are six images. Three of them are classified correctly, while three of them are incorrectly classified. One of them has been classified as an apricot, and two of them fall into class 4 (orange). (Apple, Apricot, and Pear) have the same precision, which is 66.7%. Figure 4 shows pressions and recalls for each class in greater detail. The overall classification accuracy of the proposed method is 75%, but some of the fruits are correctly classified, like oranges and lemons, in classes 4 and 5, as shown in table 3.

Table 3: Result of Fruit Classification System

No of class	Name of fruits	Classification Accuracy in %
1	Apple	66.7
2	Apricot	66.7
3	Pear	66.7
4	Orange	100
5	Lemon	100
6	Peach	50
Overall Accuracy		75

The results above are for the 35 features that were chosen out of the 10,000 features that were extracted by PCA. tables show the results of the precision and recall of all fruits when the number of features was changed.

Table 4: Result of Class 1 (Apple) in Different Number of Features.

Class 1	No. of Features	Precision	Recall
Apple	35	66.7%	100.0%
	25	66.7%	100.0%
	15	66.7%	100.0%
	5	33.3%	100.0%
	3	16.7%	100.0%

Table 5: Result of Class 2 (Apricot) in Different Number of Features.

Class 2	No. of Features	Precision	Recall
Apricot	35	66.7%	66.7%
	25	66.7%	66.7%
	15	66.7%	66.7%
	5	66.7%	50.0%
	3	66.7%	44.4%

Table 6: Result of Class 3 (Pear) in Different Number of Features.

Class 3	No. of Features	Precision	Recall
Pear	35	66.7%	100.0%
	25	66.7%	100.0%
	15	83.3%	100.0%
	5	66.7%	100.0%
	3	66.7%	100.0%

Table 7: Result of Class 4 (Orange) in Different Number of Features

Class 4	No. of Features	Precision	Recall
Orange	35	100.0%	50.0%
	25	100.0%	50.0%
	15	100.0%	50.0%
	5	100.0%	54.5%
	3	100.0%	54.5%

Table 8: Result of Class 5 (Lemon) in different number of features

Class 5	No. of Feature	Precision	Recall
Lemon	35	100.0%	85.7%
	25	100.0%	85.7%
	15	100.0%	100.0%
	5	100.0%	85.7%
	3	100.0%	85.7%

Table 9: Result of Class 6 (Peach) in Different Number of Features

Class 6	No. of Features	Precision	Recall
Peach	35	50.0%	100.0%
	25	50.0%	100.0%
	15	50.0%	100.0%
	5	50.0%	75.0%
	3	50.0%	75.0%

By testing over and over, it was found that 35 was the best number of parts for the PCA. This number was found through a series of tests, so a small change in the number of parts would make the results worse. In figure 5 below, one can see what proportion of the variance each of the principal components explains.

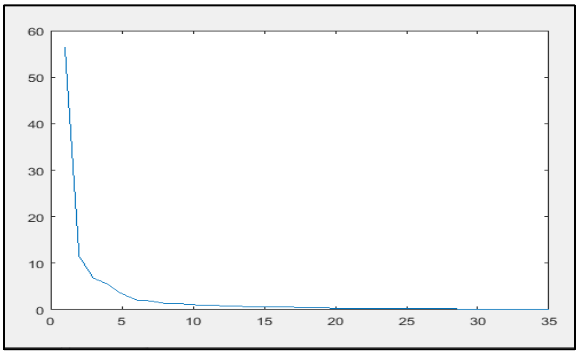


Figure. 5. A visualization of how much of the total variance each of the top 35 principal components explain. All together these principal components explained 75% of the total variance.

5.3 Dissuasion

To create and train the system, 36 of the gathered fruit photos were used. Using the six test fruit photos, the fruit recognition system was put to the test. Additionally, every test fruit image can be recognized by the system. Table 3 to 8 summarizes the recognition results of precision and recall for each class for a different number of features of the fruit recognition system on the fruit images that are being sent in as input images from the dataset. The overall rate of accuracy, as shown in figure 6 When the number of features is equal to 15, the system gives high accuracy (77.7%). And the low rate of accuracy is 66.61% when the number of features is 3.

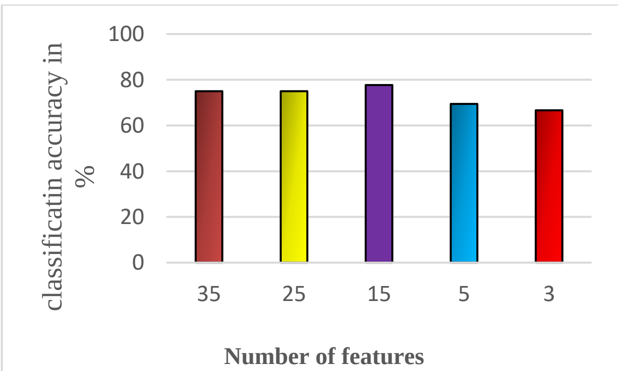


Figure 6: Classification Accuracy Under the Different Number of Features.

6. Conclusion

Automatically recognizing fruits using machine vision is considered a challenging task due to the similarities between various types of fruits and external environmental changes (e.g., lighting). Based on the extraction of PCA features, the suggested technique can process, evaluate, and recognize fruits. The experiments database, on the other hand, was extracted from the 360 dataset and used in this system. To increase flexibility and functionality, the suggested method recognized photos of fruits with ease. On the system's dataset, experiments were run, and the results revealed that the system's classification system had a 75% accuracy rate. In the future, the dataset can add more fruit classes and focus on finding fruits, figuring out where they are, and putting them into sub-classes.

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