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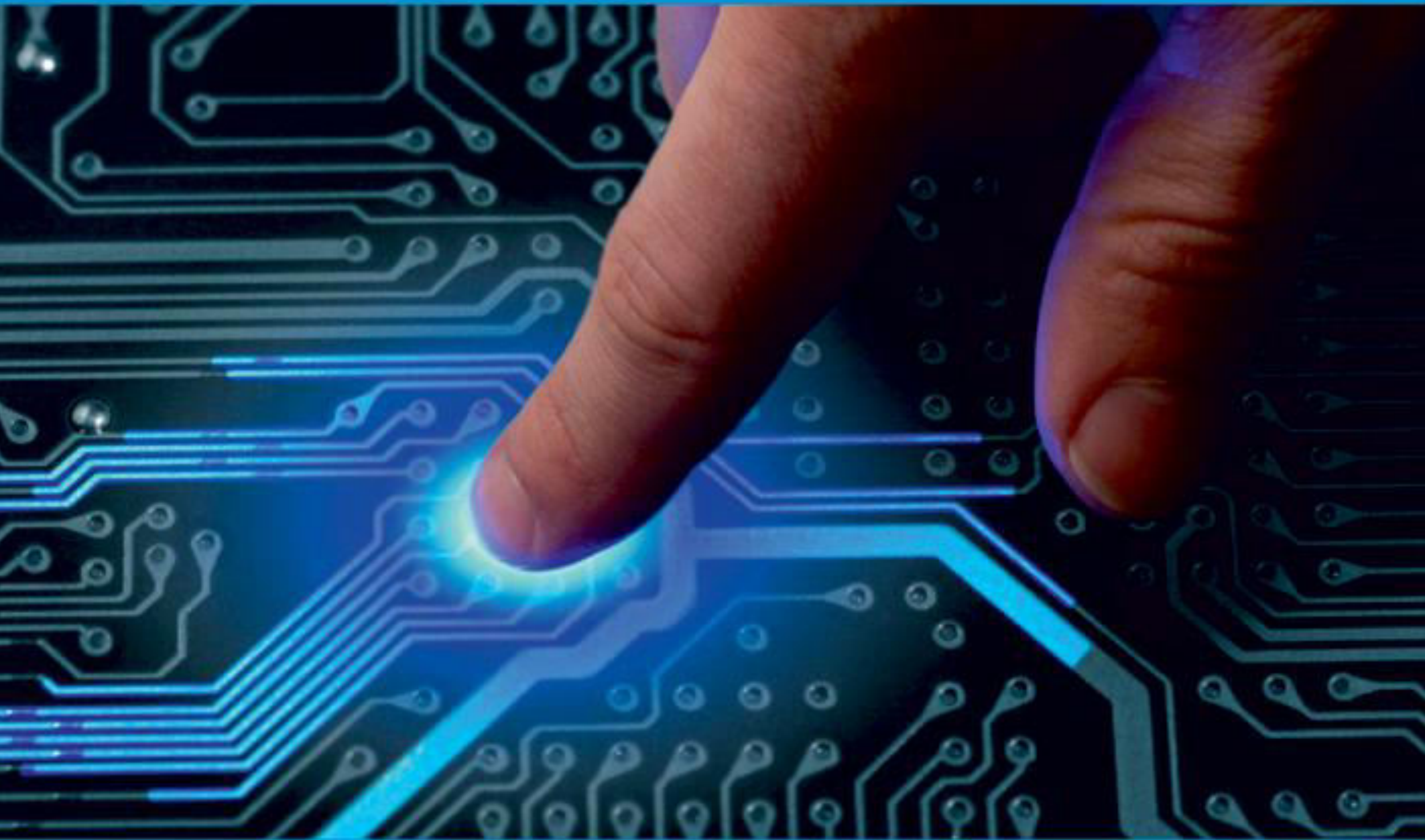

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Survey on Fruit Freshness Analysis

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ABSTRACT: Automatic classification of food freshness plays a significant role in the food industry. Food spoilage detection from production to consumption stages needs to be performed minutely. Traditional methods which detect the spoilage of food are slow, laborious, subjective and time consuming. As a result, fast and accurate automatic methods need to be introduced to in- dustrial applications. This study comparatively analyses an image dataset containing samples of three types of fruits to distinguish fresh samples from those of rotten. The proposed vision based framework utilizes histograms, gray level co-occurrence matrices, bag of features and convolutional neural networks for feature extraction. The classification process is carried out through well- known support vector machines based classifiers. After testing several experimental scenarios including binary and multi-class classification problems, it turns out to be the highest success rates are obtained consistently with the adoption of the convolutional neural networks based features.

KEYWORDS: fruit freshness classification; fruit classification; feature extraction; support vector machines.

I. INTRODUCTION

Every living being on earth is essentially dependent on nutrition to stay alive. Each individual cell needs energy to continue its vital activities such as growth, development and renewal of damages [1]. Most of the living beings obtain the re- quired energy from the nutrients they eat. Specifically, human- beings receive the energy needed by consuming food such as meat and meat products, fruits and vegetables. However, these mentioned sources of energy are also attractive to other living organisms, such as bacterias. While environmental conditions, for instance humidity and temperature allow organisms to spread inside food, these bacterial activities cause unwanted food spoilage which may be harmful for the human health. Ac- cording to Centers for Disease Control and Prevention (CDC), nearly 125 thousand United States citizens are hospitalized and 3 thousand of them suffer and lose their lives every year because of the food-borne illnesses [2]. Furthermore, more people are becoming vulnerable to spoiled food as the popula- tion of Earth increases exponentially. Therefore, detecting food spoilage from production to consumption stages is very crucial. There is indeed an urgent need for fast and accurate systems, while conventional spoilage detection techniques are slow and time consuming [3]. As a result, new vision based techniques and algorithmic approaches have been proposed in the last decades. The most recently developed methods for detecting food spoilage are based on both digital image processing and state-of-the-art machine learning, which have already proven their high potential in the food industry [4].

Since the first emergence of successful machine learning algorithms, diverse techniques have been proposed for distinct applications [5]. Fresh and rotten fruit classification is among these studies which commonly employs different techniques, like regression trees [6], support vector machines (SVMs) [7] and Fisher Linear Discriminant Analysis (Fisher-LDA) [8] to enhance the classification rate. For instance in [9], the aim was to identify and classify different fruits and vegetables using machine learning tools. A dataset was collected with 15 distinct fruits and vegetables, taken at various times of different days to ensure real life conditions. Although the back- ground of all images was the same, some of the samples had shadows. Thus, K-means based background subtraction was first employed. Different types of algorithms such as SVMs, LDA, classification trees, K-nearest neighbors (K-NNs), and ensembles of trees together with LDA were later adopted to obtain the best performance for this dataset. According to the experimental results, SVMs and LDA demonstrated the best performance, whereas the average error of SVMs was much lower than that of LDA. In [8], the proposed study was related to the detection of fruit defects in retail. Sample images of oranges which move on a conveyor were acquired by means of two cameras placed on the sides. Color was chosen as a feature in RGB color space and color histograms were calculated. In order to eliminate the noise and reduce the dimensionality of the feature space, Fisher-LDA was adopted. The regions of defects on oranges were successfully determined using SVMs with a recall rate of 96.7%. In [10], another study was carried out for the fruit and vegetable classification and recognition problem (with 18 categories) in supermarkets. To locate fruits and vegetables in images, background subtraction through a split-and-merge algorithm was employed before ex- tracting color, texture and shape features. Principal Component Analysis (PCA) was adopted to reduce the dimensionality of the feature space. Winner-Takes-All (WTA) SVMs (as one-versus-all approach), Max-Wins-Voting (MWV) SVMs (as one-versus-one approach) and

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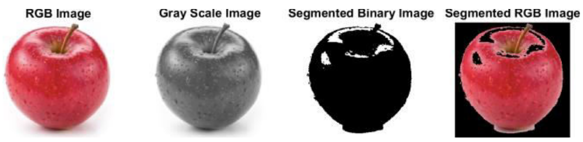
Directed Acyclic Graph (DAG) SVMs based classifiers with homogeneous polynomial (HPOL), inhomogeneous polynomial, Gaussian radial basis (GRB) and hyperbolic tangent kernels were tested for clas- sification. Experimental results indicate that the best success rates were obtained by MWV-SVMs using GRB kernel with an accuracy of 88.2%. Yet another study in [7], an algorithm to differentiate between rotten and fresh fruits is proposed. A dataset of apple images was first contrast limited adaptive



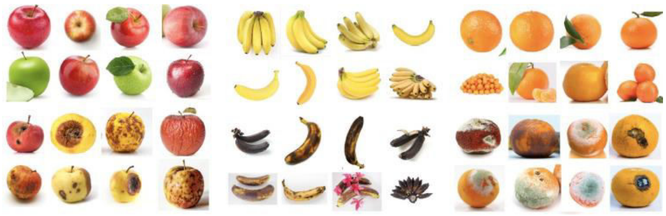


Figure 1: Example image samples from [14] used in this study.

histogram equalized to enhance the quality of images and tex- ture features were extracted through Gray Level Co-occurrence Matrix (GLCM), Wavelet transformation, Tamura, Histogram of Oriented Gradients (HOG) and Law's Texture Energy (LTE) feature descriptors. The obtained features were classified with SVMs, K-NNs, logistic regression and LDA. SVMs presented the highest accuracy with 98.9%. In [6], a system was designed to detect rottenness caused by microbacterial activities in fruits. This proposed novel approach was related to the spoilage of the fruits using the hyperspectral imagery for defect segmentation. The reported experimental results demonstrate that rottenness levels of the fruits can be successfully assessed with the clas- sifiers based on artificial neural networks (ANNs) and decision tress. In [11], a study was carried out to detect surface defects on tomato samples from color and texture features using PCA and SVMs. Tomato image samples were analyzed in RGB and HSV color spaces in which statistical features were extracted from. The proposed system was successful to detect texture defects with an accuracy rate of 92%. Another study proposed in [12] was performed for fruit and vegetable recognition using image texture and color features extracted from 15 distinct fruits and vegetables such as plum, Agata potato, Asterix potato, cashew, onion, orange, Taiti-lime, kiwi, Fuji apple, Granny-Smith apple, watermelon, honeydew melon, nectarine, Spanish pear and diamond peach. Color features such as global color histograms, color coherence vector, color difference histograms, structure element histograms, local binary pattern, local ternary pattern and completed local binary pattern were utilized with multi-class SVMs, while applying background subtraction to improve the success rates. Additionally, ultra- violet (UV), near-infrared (NIR) and fluorescence (FL) vision systems were combined in [13] to identify and classify skin defects of citrus fruits according to forms of defects. UV enables a complete detection of stem-end injury, and FL and NIR let the identification of anthracnose and green mould to be around 95% success.

This study proposes a comparative analysis on several feature extraction methods and algorithms for the classification of fresh and rotten fruits problem. The main aim here is to compare and report success rates of different methodologies using a publicly available dataset in [14] containing fresh and rotten apple, banana and orange images. Some example image samples are demonstrated in Figure 1 from this dataset. Several features are extracted from these images and classification is accomplished through SVMs based classifiers in order to analyse the effectiveness of the extracted features.

The remaining part of this paper is organized as follows. Section II describes the methods of segmentation and feature extraction algorithms together with SVMs classifier used in the Figure 2: An example apple segmentation result. Segmented image is later used for feature extraction.

experiments. Section III reports and discusses the experimental results obtained. Finally, Section IV concludes the paper with a brief conclusion on the fresh and rotten fruits classification problem.

II. METHODOLOGY

A. Segmentation

Segmentation plays a vital role for obtaining high clas- sification accuracy rates. The well-known and effective seg- mentation technique based on image histograms called Otsu's method [15] is employed in this study. An example segmenta- tion result is demonstrated in Figure 2. After segmenting the fruit from the background, specific features are extracted in the segmented fruit region of the image.

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B. Feature Extraction

Four different feature extraction methodologies are adopted as follows.

Histogram Features (Hist). Histograms are commonly pre- ferred as features in classification tasks with large number of observations [7], [8], [12]. Therefore, gray-scale histograms of images are extracted as features.

Gray Level Co-Occurrence Matrix. GLCM demonstrates how often distinct gray level combinations of pixels are present in an image [16]. It is generally employed in image classification as a statistical technique where energy, contrast, correlation and entropy are some examples of features gathered using this method. This paper focuses on the energy features extracted through GLCM. To compute the GLCM, a horizontal offset group that exclusively change in distance of size 256 1 is formed.

Bag of Features (BoF). BoF is an adaptation of the bag of words to extract features for computer vision tasks [17]. Images do not contain discrete words, however, they have discrete pixel based features [17]. Therefore, a vocabulary can be constructed for each image class. The BoF algorithm extracts features from all images in these categories using the SURF method [18]. Then, K-means clustering is applied to reduce the number of features and to select the strongest features suitable for the task in order to create a visual vocabulary [17].

Convolutional Neural Networks (CNNs) Features. CNNs are powerful deep learning methods used in image processing, machine learning and computer vision problems [19]. Clas- sification of images, object recognition and digital character recognition are some examples of fields where CNNs have already been adopted successfully [20]. A CNNs simple archi- tecture mainly consists of an input layer, a convolutional layer,a pooling layer and a fully connected layer [20]. The number of layers changes according to the complexity of the studied task. In complex applications, the number of these mentioned layers tend to increase.

In this study, image features are extracted through CNNs by using ResNet-50 [21] as the pretrained network to reduce computational time. A mini-batch size of 32 is preferred after observing that higher batch sizes result in poorer accuracy rates and higher computational times. Fundamental image features such as blobs and edges (low-level features) as well as small details (high-level features) are extracted through CNNs. The features obtained through CNNs are abbreviated as CNNsF in the remaining part of this paper.

C. Classification

In order to ensure the consistency between all experiments, dimensions of the extracted features are kept fixed of size 256 elements. Moreover, all feature vectors are normalized before the classification process. Both binary and multi-class SVMs are used to classify each label with different experimental scenarios. The best side of SVMs is that both linearly and non-linearly distributed data can be classified with high ac- curacy rates. For non-linear distributions, the most frequently used kernels are linear kernel, radial basis function (RBF), polynomial kernel (POLY), sigmoid kernel, and more [22]. The selected type of kernel is indeed crucial to improve the classification accuracy, and it should be kept in mind that different kernel types may give different accuracy rates for the same dataset.

III. EXPERIMENTAL RESULTS

As mentioned before, the publicly available dataset from [14] containing fresh and rotten apple, banana and orange image samples is used in the experiments (see Figure 1). First of all, some impractical image samples with noise and rotation are eliminated from this dataset, which indeed conflict with the aim of this study. The total number of the remaining images is 1200 where there are 200 images for each six distinct classes, i.e., fresh apples, rotten apples, fresh bananas, rotten bananas, fresh oranges and rotten oranges. Moreover, all these image samples with different spatial resolutions are resized to 256 256 pixels. SVMs classifiers are utilized with RBF kernel, 10-fold cross-validation is employed for testing, the performance of each system is evaluated according to the derived confusion matrices, all experiments are repeated five times and the mean success rates are provided in this paper. A general block diagram of the experimental setup is given in Figure 3.

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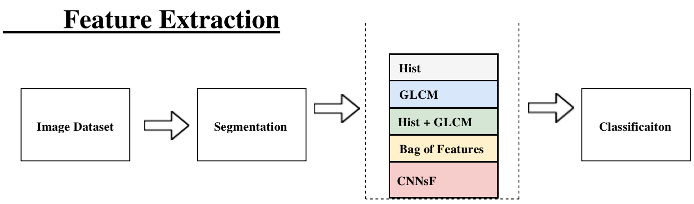

Figure 3: A general block diagram of the experimental setup.

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Fruit Type	Hist	GLCM	Hist+GLCM	BoF	CNNsF
Apple	80.50	71.00	77.25	71.83	97.00
Banana	97.50	74.00	86.37	73.17	99.83
Orange	87.50	82.50	86.12	84.03	97.50
Average	88.50	75.83	83.25	76.34	98.11
All Fruits	83.08	70.67	74.46	75.19	96.78

Table I: Success rates of different features with SVMs (%). Classification among fresh and rotten samples: each fruit type is trained with one binary-SVMs classifier per feature type.

In the first set of experiments, binary-SVMs classi- fiers based on four respective features, plus one additional Hist+GLCM (the concatenation of Hist and GLCM features), are trained to classify fresh and rotten samples for each individual fruit type. As it can be observed from Table I, the highest accuracy rate is reached for distinguishing fresh bananas from those of rotten with 99.83% using CNNsF. The experimental results indicate 97.50% and 97.00% success for oranges and apples using CNNsF features, respectively. These reported results are obtained from five different classifiers trained over three different fruit categories leading to an average of 98.11%, 88.50%, 83.25%, 76.34% and 75.83% success rates for CNNsF, Hist, Hist+GLCM, BoF and GLCM, respectively.

Yet a new binary classifier is trained to identify fresh fruits from rotten samples directly, with labeling all fresh fruits as one class and all rotten ones the other. The CNNsF based system this time achieves a success rate of 96.78% (Table I, last row), which is naturally lower than the accuracy rates reached for classifying each individual fruit separately. Interestingly this setup has higher accuracy than the classifier trained specifically for apples with Hist features, and than the classifiers trained specifically for apples and bananas with BoF features. In addition, utilizing Hist+GLCM features develops an efficiency of the system leading generally to better success rates when compared to GLCM alone and BoF alone. It is apparent that GLCM feature concatenation reduces the success rates of Hist features. This observation results in a conclusion that combining more features might (or not) demonstrate higher efficiency for this task. It is worth mentioning here that both the success rates (as can be seen in Table I) and the processing time do not match the desired outcomes with BoF features. The BoF algorithm requires a long processing time, up to 100 iterations per class and each iteration takes at least 8sec. As a result, the complexity of BoF is expensive for this task and importantly, the performance of the system does not make up for this disadvantage. As a final note here, this part of experimental results lead to a conclusion that without knowing the fruit type (i.e., without employing another algorithm for fruit classification), it is highly possible to differentiate the fruit freshness or rottenness stages using CNNsF.

In the second set of experiments, one-vs-all SVMs classi- fiers are employed based on respective features (as in Table I) in order to investigate the success rates of identifying one class among the others. Assuming that there are six individual classes as reported in Table II, one striking observation is that Hist+GLCM features present improvements when compared to success rates of these individual features alone. While CNNsF still provides the best performance with the accuracy of

Fruit Class	Hist	GLCM	Hist+GLCM	BoF	CNNsF
Fresh Fruits	95.83	99.00	95.83	92.22	99.78
Rotten Fruits	94.50	97.67	91.42	76.48	98.60
Average	95.17	98.36	93.63	84.35	99.19
All Fruits	93.83	96.42	88.92	73.95	96.72

Table III: Success rates of different features with SVMs (%). Classification among fruit types: each fruit class is trained with one multi-class SVMs classifier per feature type. “Fresh Fruits” has three classes, “Rotten Fruits” has three classes, and “All Fruits” has six classes.

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Fruit Class	Hist	GLCM	Hist+GLCM	BoF	CNNsF
Fresh Apple	89.25	85.17	93.29	84.94	98.67
Fresh Banana	96.83	89.75	97.04	89.55	99.33
Fresh Orange	93.92	89.75	95.04	90.97	96.50
Rotten Apple	89.67	85.75	96.33	81.78	96.67
Rotten Banana	94.00	87.67	96.00	90.44	99.67
Rotten Orange	87.67	84.67	94.08	75.83	94.83
Average	91.89	87.13	95.30	85.58	97.61

Table II: Success rates of different features with SVMs (%). Classification of one class among all other samples: each fruit class is trained with a one-vs-all SVMs classifier per feature type.

97.61%, the concatenated Hist+GLCM demonstrate promising results with 95.30% on average. Additionally, BoF presents the poorest performance for this experimental setup in terms of both average success rate and the computational time (which requires 14sec per iteration).

To extend the scope of this study, one last set of experi- ments is carried out with multi-class SVMs to classify three types of fresh fruits (with a three-class SVMs), three types of rotten fruits (with a three-class SVMs) and all six classes with a six-class SVMs. As can be observed from Table III, a general poor performance is obtained through BoF in terms of both success rates and computations when compared to other feature types. In contrary to previous experimental observation, Hist+GLCM features present worse results indicating that this concatenation is not suitable for this classification task, especially for the six-class case resulting in a success rate of 88.92% (Table III, last row). Moreover, GLCM features provide higher success rates than Hist in these multi-class setups. While CNNsF still provides the best performance with average success rates of 99.19% and 96.72% for three- and six-class problems respectively, GLCM features demonstrate a close performance with 98.36% and 96.42% on average.

IV. CONCLUSION

Automated vision based systems to distinguish fresh and rotten fruits (also among different fruits) would significantly decrease food waste, diseases related to food-borne and eco- nomic loss [2]. In this study, a performance analysis of different feature extraction techniques combined with SVMs classifiers has been performed for the addressed problem of classifying fresh and rotten fruit images taken from [14]. While comparing classification success rates of several features (such as Hist, GLCM, BoF, CNNsF) for different but very related tasks, CNNs appear to be the most successful feature extractors, as further have proven their efficiency in such applications. The concatenation of Hist and GLCM features leads to promising results for some classification tasks. There- fore, concatenation of different types of proper features might produce more successful and robust systems.

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