# A Survey of Product Recognition in Shelf Images


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***Abstract*—Nowadays, merchandising is one of the significant method which allows to increase the sales. Therefore, activities such as monitoring the number of products on the shelves, completing the missing products and matching the planogram continuously have become important. An autonomous system is needed to automate operations such as product or brand recognition, stock tracking and planogram matching. In the literature, it is seen that many studies have been carried out in order to address this issue. This survey classifies and compares all existing works with the aim to guide researchers working on merchandising.**



***Keywords—product recognition; planogram matching; brand recognition; stock tracking***


## I. Introduction

Every kind of activity, technique and method applied in the store in order to direct the purchases by influencing the consumers is defined as merchandising. Merchandising includes activities such as retail store display which can be done in such a way to maximize customers' interest; moreover, goods can be placed in the most appropriate location for the traffic flow at the store, in order to increase the availability, visibility and affordability of the products [1]. According to the survey of POPAI (Point of Purchase Advertising International), the rate of shoppers who decide to make purchases within the retail store is 66.1% in 1986, 70% in 1995, 76% in 2012 and 82% in 2014 [2]. The increase in this ratio indicates the importance of merchandising.

An important part of mechantising is planograms; it is a schemes that indicates the ideal arrangement of market shelves, with the aim to maximize sales of retail products. According to [3], when optimized planogram was 100% matched, sales increased by 7.8% and profit by 8.1% within two weeks. Therefore, it is very important to control the placement of the product according to planogram as well as the creation of good planograms. Furthermore, as reposterd by [4], 31% of the customers who can not find the desired product on the shelf receive the same product from another market, 22% of them take the different brand of the same product, and 11% of them give up the product when they cannot find it. For this reason, it is necessary to follow the number of products on the shelves, complete the missing products and to maintain the compatibility of the planogram.

Nowadays, all these operations are done manually by staff members who analizes the pictures of the markets' shelfs regulary. Therefore, there is a need for an automated system that will provide an interface between retailers, producers, distributors and customers, which can be realized more quickly and reliably. On the other hand, all these processes are compelling problems of the computer vision field because most of the products on the shelf are visually similar in shape, color, texture and size [5]. In the literature, it is seen that several studies related to planogram matching, product recognition, brand recognition and stock tracking have been carried out in order to solve this issue. This survey will guide the researchers to work on this issue by making classification and comparison of all present works.

## II. Classification of Product Recognition Systems

When we look at the literature about planogram matching, product recognition, brand recognition and stock tracking, it is seen that there are many different studies using remote sensing technologies [6, 7, 8, 9, 10, 11], and, in alternative, computer vision approaches [12, 5, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24].

### A. *Overview of the Studies using Remote Sensing Technology*

In the literature, RFID (Radio Frequency Identification) tags [8, 9, 10, 11], sonar [6] and infrared [7] sensors were used in remote sensing technology. However, recent studies show that this approach has some limitations. That is, a system consisting of RFID tags has a high investment cost [8, 9, 10, 11], while sonar and infrared sensors are not very effective in closed environments [6, 7]. Moreoveer, an obstacle found in a complex environment can cause the reflected echoes to be distorted and, therefore, it may cause unreliable information to be transmitted. For this reason, the number of studies benefiting from the advantages of computer vision approaches is increasing, and this survey focuses on the computer vision approaches.

### B. *Overview of the Studies Using Computer Vision Approaches*

The two main approaches proposing solutions to the mechandising issues are based on finding the same products on the shelf [14, 18, 20] or on classification [12, 5, 13, 15, 16, 17, 19, 21, 22, 23, 24].

All studies based on finding the same products on the shelf without making classification require different inputs instead of the training set. The major works following this approach are [14, 18, 20].


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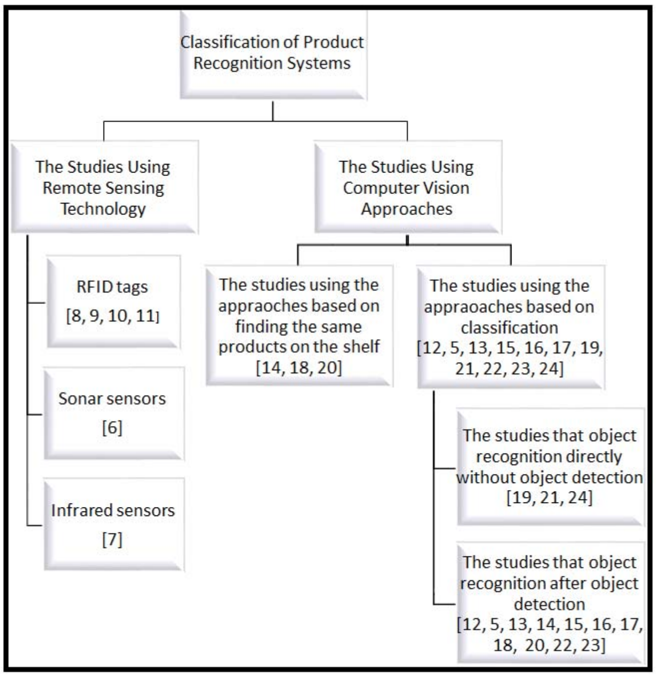


Fig. 1. Classification of Product Recognition Systems

Studies [14] counts the products and detects the missing items. The system input is the "region of interest" (ROI) and the label of the product which is selected by the user. The system calculates the number of the same items presents on the shelf using the morphological properties of the selected product and those of other items in the shelf image, template matching for ROI and label, comparison of HSV color histograms. Success of the system is about the distinctiveness of selected labels belonging to the same brand. For this reason, the results as worst case, moderate case and best case were examined separately. In all products, the success of worst case is 87%, the success of middle case is 97%, and the success of best case is 100%.

Two different methods have been presented in the robot-based retail stock assessment study [18]. Firstly, a k-dimensional tree is created from the SURF (Speeded-Up Robust Feature) descriptors for each product template. In the first method, each item of the product is counted considering the reproducibility of the properties obtained from SURF descriptors. In the second method, each product is identified with a rectangle box with SURF and color properties. The RANSAC (RANdom SAmple Consencus) algorithm is used to extract the ROI that matches the product templates from the image. The first method achieved 74.9% and the second method 72.47% success on 861 images of 22 different products obtained by the robot. The first method achieved 98.86% and the second method 97.36 % success on 370 images of 24 different products obtained by a telephone camera. The cause of the low success on the images obtained by the robot is about the quality of the images. Also, when enough number of SURF descriptor was found in the products, the system was working well.

The study of [20] uses as system inputs planogram information such as number of shelves, number of products per shelf, and product type; in this work shelf images consist of 7 product types with different number, different product sizes and different qualities. In the image, pattern recognition is performed by binary visual word-object mapping in the areas reserved for each product. The spectral graphical compatibility is matched between the planogram information and the model obtained from the shelf image. The highest score of Greedy algorithm is accepted for product matching**.** On the shelf image, results were obtained according to product numbers, product dimensions and product qualities. According to results, large size, high quality and a large number of products increase the success of the system.

Classification-based approaches can be grouped into the studies that performed directly object recognition without object detection [19, 21, 24], and the studies that performed object recognition after object detection [12, 5, 13, 14, 15, 16, 17, 18, 20, 22, 23]. For a small number of products the first approach is sufficient to exclude existing or absent knowledge, but it is not effective in systems that require high accuracy, or when the number of products detected and their location in the shelf are concerned [16].

Study [24] proposed an application for visually impaired users which performed directly object recognition, with the aim to find the products present in a shopping lists from video images of retail shelfs. As training set, 52 different products and some back ground images were taken from the Grozi-120 dataset. Products were recognized with SURF identifiers, which is faster than other descriptors, and color histograms, and they were classified using the Multi-Class Naive Bayes classifier. The success of the system was measured by detecting 25 different shopping lists in 10 different video images. The number of products that are missed increases as the threshold for getting the right product increases. In summary, the correct threshold for object recognition was not found.

Study [21] used the same data set as [24]; the system performance was measured on 10 situ (frames of videos come from natural environments) images by the model obtained from SIFT (Scale-Invariant Feature Transform), Boosted Haar-like features and Color Histogram Mapping features which were trained on the 10 vitro images (isolated and captured under ideal imaging conditions). According to results, the order of success of the methods is SIFT, then Color Histogram Mapping, and, finally, Haar-like features.

In another study [19], the logo recognition on the real life images is performed directly on the image. A property point is determined by the Harris-Affine method and this is indicated by the SIFT descriptor for the 7 different brands. These descriptors were clustering with hierarchical k-means cluster in tree structure. Then, association rules are established for each brand with apriori algorithm. The performance of the system was measured with 6-fold cross-validation on 1000 real-life images. The study was not successful on the recognition of brands that take up little space in the image, but it was successful on recognition of brands that have more examples.

In the remaining of this paragraph we considered the major works performing object recognition after object detection.

Studies [13] and [22] aimed to determine if the sequences of the products on the shelves are compatible or not with the planogram sequences. Hough transformation is used for shelf detection and HOG (Histogtam of Gradients) features classified with Cascade Object Recognition algorithm are used for product detection. Shelves were correctly detected with a rate of 83.4% on the 229 shelf images containing only cigarettes. Products were detected with 88.8% precision value and 87.9% recall value on 573 examples obtained from 291 different product location. In addition, HOG and Color Histogram features obtained from 134 brand images were classified with SVM (Support Vector Machines) for brand recognition [22]. The rate of 96% is obtained from the test on 55 brand images.

Study [23] used shelves images consisting of cigarette packets, and used for product detection the same methods as in studies [13] and [22]. The difference from the other studies is that the elimination of misidentified products has been provided. Products were detected with 81% precision value and 94% recall value on 573 examples obtained from 1300 different product locations on 354 shelf images. Shape descriptors are extracted with SIFT and color descriptors are extracted with HSV (Hue, Saturation, Value) on 274 items belonging to 10 different brands. These descriptors are classified with SVM for brand recognition. With a test set of 700 samples, the performance of 85.9% was achieved when shape features were used only, 60.5% when color features were used only, and 92.3% when both were used. The cause of the reduction of the precision value according to [13] and [22] is the elimination of overlapping product images due to making some products undetectable. The cause of the reduction of the rate of brand recognition according to [22] is increasing the number of brand.

Study [16] is aimed to determine product boxes by using two separate methods which consist of preprocessing, line detection, line-based elimination, and elimination of overlapping products steps. In the preprocessing step, product boxes were determined using the mean size filter and the median size filter after the Cascade Object Recognition algorithm. In the line detection step, Gaussian Filter was used in first method and Gaussian Mixture Model was used in second method. In the steps of line-based elimination and elimination of overlapping products, different distance metrics were used. It takes the shelf image consisting of cigarette packects, the number of rows and columns in the planogram as input. These two methods and results on 200 shelf images are shown in the Table III. Though the performance ratios of the two methods are close to each other, slight differences were found in their techniques. According to the results, the false positive rate of the first method is lower than the false negative rate of the second method.

Study [15] improved the method described in [16] for product detection. Brand recognition is processed on the upper 40% of the cigarette packets in which the brand distinguishing characteristics are present. Classification with ELM (Extreme Learning Machines) is performed by extracting shape-based Fisher vector obtained from the features of DenseSIFT, color histogram and Local Binary Pattern information on this area. A success rate of 99.21% was obtained in the recognition of 13 different brands. Study [15] gets a higher score from the algorithm developed for the recognition of 10 different brands in [23].

A hybrid classification system consisting of two main parts has been presented in [5]; this work tackles the issue of distinguish similar products. In the first part, classification is made by SVM using the information obtained from the retail product image. In the second part, the classifications obtained in the first section are combined with the learned statistical product sequence model and the product classes are extracted. These two methods were tested on datasets consisting of 108090 soft drinks product images with 794 different classes of 11557 horizontal shelf sequences that do not overlap. According to the result of study on difficult products with high similarity, the developed hybrid system is more successful than the other method.

Study [12] is aimed to classify products belonging to different categories. Vi-Co-Net is proposed as a model of inference chart that models the link between retail products on the stage. In this graphical model, objects are represented as nodes and are connected to each other by edges when viewed together on a visual scene. The weight of a node is a function of the number of times the object is seen. An edge weight between any two nodes is a function of the number of co-occurrences of these two objects. The test was conducted on 11 different classes with 73% success rate. However, this study has been tried to be improved the efficiency rather than the classification success.

Unlike the other studies, object recognition was performed on images of 6 different beverage types (CocaCola, Coffee, Fanta, Pepsi, Mineral Water, and Coconut Water) in the study [17]. Firstly, the object which is separated from the image background with the Saliency Map followed by the Mean Shift Segmentation is passed through the HSV color-based threshold. The feature vectors obtained by color and SURF descriptors from training datasets with 195 examples were classified by SVM. The 89% success is obtained on test data with 194 examples.

## III. Comparison of studies' results

The results of the classified studies are given separately on tables. Comparison of the studies using the appraoches based on finding the same products on the shelf without classifying is shown in Table I. As it can be seen in Table I, studies have different success rate according to type of data, inputs of the system, test dataset and methods used. Three different tables are created for the comparison of the studies using the appraoaches based on classification. The comparison of the studies that object recognition directly without object detection is shown in Table II. As it can be seen in Table II, studies can't achieve a significant success rate. Therefore, object recognition directly without object detection is not a very efficient method. Comparison of the studies that object recognition after object detection for cigarette packets is shown in Table III. These studies are the continuation of each other and are based on the development of algorithms and the enhancement of success. Study [15] obtains the best results in shelf detection and brand identification; however, for the presence of the product

TABLE I. THE STUDIES USING THE APPRAOCHES BASED ON FINDING THE SAME PRODUCTS ON THE SHELF WITHOUT CLASSIFYING

| The Studies | | The Type of Data | The Inputs of Sytem | Test Dataset | Methods | Success Rates | |
|---|---|---|---|---|---|---|---|
| [14] | | Shelf image consist of different products | ROI and label of product to be searched on shelf | 100 items selected by the user on the shelf image | Heuristic Algorithm (Morphological Operations + Template Matching + Comparison of HSV color histograms + Threshold) | Worst Case : 87%<br>Middle Case: %97<br>**Best Case: %100** | |
| [18] | Method 1 | Images obtained from robot | Product template | 861 images consist of 22 different product | SURF | %74.95 | |
| | | Images taken by phone | | 370 images consist of 24 different product | | **%98.86** | |
| | Method 2 | Images obtained from robot | Identification of each product from image with a rectangular box | 861 images consist of 22 different product | SURF + Color Histogram+ RANSAC Algorithm | %72.47 | |
| | | Images taken by phone | | 370 images consist of 24 different product | | **%97.36** | |
| [20] | | 7 product types in different product sizes, different product numbers and different qualities | The number of shelves in the planogram, the number of products and product type on each shelf | Planogram image and shelf image to match | Binary Visual Word-Object Mapping + Spectral Graphical Mapping + Greedy Algorithm | Product Size | **Big-%95.32**<br>Medium-%90.61<br>Small-%85.24 |
| | | | | | | Product Quantity | Large-%87.57<br>Medium-%88.19<br>**Small-%93.49** |
| | | | | | | Feature Quality | **Rich-%96.03**<br>Medium-%91.77<br>Poor-%89.24 |

TABLE II. THE STUDIES THAT OBJECT RECOGNITION DIRECTLY WITHOUT OBJECT DETECTION

| The Studies | | The Type of Data | Train Dataset | Test Dataset | Methods | Success Rates |
|---|---|---|---|---|---|---|
| [21] | Method 1 | 120 different product (Grozi-120 dataset) | 10 vitro images | 10 situ images | SIFT | %88.0 |
| | Method 2 | | | | Matching Color Histogram | %60.0 |
| | Method 3 | | | | Boosted Haar-like features | %33.0 |
| [19] | | 7 different brand | 6-fold cross validation over 1000 real world scenes. | | Brand recognition:<br>SIFT +Bag of Words + Apriori Algorithm | Not successful - on brands take little space in the image<br>Successful – on brands that have more examples |
| [24] | | 120 different product (Grozi-120 dataset) | 52 different products + background images | 25 different shopping lists with 10 item on 10 different video images | Optical Flow Algorithm + SURF+ Color Histogram + Multi Class Naive Bayes Classifier | There was not found the correct threshold for object recognition. |

location, works [15] and [16] provides advantages in different situations. Comparison of the studies that makes objectrecognition after object detection for different products is shown in Table IV. More complex problems (Multi-class problems with more product varieties) have been addressed in the studies of [12], [5] and [17] on the success of the system as a whole.

Each study achieved significant results on different data sets. Performance of the studies in the Table III is higher than the results of the studies in the Table IV because cigarette packets are easy to recognize from other products.

## IV. FINDINGS OBTAINED FROM THE LITERATURE REVIEW

When the majority of existing studies are examined, the following results were obtained:

- The approach of object recognition directly without object detection is easier and faster than the approach of object recognition after object detection
- SURF descriptor is faster and more robust than SIFT descriptor
- Cascade Object Detection Algorithm is successful in objects whose aspect ratio is fixed or slightly change
- The Algorithm of RANSAC is an appropriate method for calculating model parameters from data sets containing a large number of outliers
- The success rate is increased by using color and shape properties of an object together
- Using together object recognition and information of sequences of products increases the success rate

Considering all examined works, we are confident in saying that, the data set is one of the important issues for the success of the studies. The main points to note about the dataset are:

- The images were taken with different cameras
- The images were retrieved from different grocery stores
- The images were taken at different distances, at different angles, and at different lights

TABLE III. THE STUDIES THAT OBJECT RECOGNITION AFTER OBJECT DETECTION FOR CIGARETTE PACKETS

| The Studies | The Type of Data | Train Dataset | Test Dataset | Methods | Success Rates |
|---|---|---|---|---|---|
| [13] | Cigarette packets | - | 229 shelf images | Shelf Detection:<br>Hough Linear Detection | %83.4 |
| | | - | 573 samples (375 positive 195 negative samples from 291 Product positions) | Product Detection:<br>Histogram of Directional Gradients<br>Cascade Object Recognition Algorithm | Precision: %88.8<br>Recall: %87.9 |
| | | 134 samples (47 positive, 87 negative logo images of 1 brand) | 55 samples (31 positive, 24 negative logo images of 1 brand) | Brand Recognition:<br>Histogram of Directional Gradients<br>Color Histogram<br>Support Vector Machines | %96.0 |
| [23] | Cigarette packets | - | 573 samples (375 positive 195 negative samples from 13000 Product positions) | Product Detection:<br>Histogram of Directional Gradients<br>Cascade Object Recognition Algorithm<br>Uncertainty Detection | Precision: %81.0<br>Recall: %94.0 |
| | | 2740 samples (274 samples from each of 10 different brands) | 700 samples (100 samples from each brand except the 3 brands have few samples) | Brand Recognition:<br>SIFT<br>HSV Color Space<br>Support Vector Machines | %92.3 |
| [16] Metot 1 | Cigarette packets | - | 200 Shelf images | Product Detection:<br>Cascade Object Recognition Algorithm<br>Gaussian Filter<br>The approach of different line based elimination<br>The approach of different conflict elimination | Precision: %96.68<br>Recall: %87.8<br>F-score: %92.2 |
| [16] Metot 2 | | | | Product Detection:<br>Cascade Object Recognition Algorithm<br>Gaussian Mixture Model<br>The approach of different line based elimination<br>The approach of different conflict elimination | Precision: %93.6<br>Recall: %94.4<br>F-score: %94.0 |
| [15] | Cigarette packets | | 573 samples (375 positive 195 negative samples from 291 product positions) | Product Detection:<br>Cascade Object Recognition Algorithm<br>Mean & Median Filter | **Precision: %94.05**<br>**Recall: %97.31**<br>**F-score: %95.65** |
| | | - | 229 Shelf image | Shelf Detection:<br>Gauss Mixture Model | **%99.03** |
| | | 3562 samples (274 samples from each of 13 different brands) | 1300 samples (100 samples from each of the 13 brands) | Marka Tanıma:<br>DensitySIFT<br>Fisher Vectors<br>Local Binary Pattern<br>Extreme Learning Machines | **%99.21** |

TABLE IV. THE STUDIES THAT OBJECT RECOGNITION AFTER OBJECT DETECTION FOR DIFFERENT PRODUCTS

| The Studies | The Type of Data | Train Dataset | Test Dataset | Methods | Success Rates |
|---|---|---|---|---|---|
| [12] | 62 different product | 4800 samples consist of 11 different class | 1000 samples consist of 11 different class | Vi-Co-Net Grafical Extraction Model | %73.0 |
| [17] | 6 different beverage types (CocaCola, Coffee, Fanta, Pepsi, Mineral Water, Coconut Water) | 195 samples | 194 samples | Product Detection:<br>Saliency Maps<br>Mean Shift Segmentation<br>HSV Color Space<br>Product Recognition:<br>SURF<br>Bag of Words<br>Support Vector Machines | **%89.0** |
| [5] Method 1: Independent of the sequence | 108090 pieces of soft drink product with 794 different products | 20% of dataset | 70% of dataset | SIFT<br>Bag of Words<br>Support Vector Machines | %68.45 |
| [5] Method 2: Dependent of the sequence | | 70% of dataset | 10% of dataset | Chain Structured Graphical Model<br>Support Vector Machines | %78.40 |

- In the images, the product and brand diversity was ensuring with a sufficient number of samples as much as the scope of the work

When the previous works are examined, there are some problems about product recognition:

- The lack of visual difference among the different products of the same brand creates problems in classification
- The images taken at different angles and at different distances, image quality, and light reflections create problems in classification
- The methods used to increase classification success can lead to incorrect product classification or the inability to classify the product

## V. Conclusion

The aim of this survey is to guide the researcher to work on the merchandising issue. In the literature, there are many studies about planogram matching, product recognition, brand recognition and stock tracking. When all these works are examined, we may say that significant results were obtained by different methods on different product groups. In this survey, all major studies have been classified according to the used approaches. Moreover, the results of the works belonging to the same group were evaluated among themselves and we also underlined the main drawbacks of the used algorithms, as well as we pointed out the main issue related to datasets.

In further studies, improvement of the methods used in the literature; implementation of a system independent of the user inputs required for the operation of the system in the literature; increasing the success of the recognition with different hybrid approaches other than used in the literature or deep learning can be proved.

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