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Medical Waste Segregation using a Fuzzy Expert System

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Abstract— **This paper introduces an automated waste segregation instrument commercially productive for laboratory applications and for medical waste recognition. In this system, a fuzzy rule based system is designed being able to segregate 24 different hospitals waste types which are selected from 8 more common medical waste groups. After capturing each frame, some preprocessing operations are done, features are extracted, fuzzy parameters, fuzzy terms and fuzzy rules are determined and finally a rule with a maximum certification degree is fired. The system is flexible on different light conditions, view degrees of the camera, and 360 degree object rotation. Our experiments on a real environment and using both new and used wastes show that the performance of the system is more than 94%. It works on different light conditions, different view degree of camera and different positions of the objects.**

Keywords-component; medical waste segregation; fuzzy expert system; fuzzy rule-based system

I. INTRODUCTION

Studies show that large hospitals generate 2.0 kg of waste, per bed per day. Of this, 0.5 kg can be categorized as biomedical risk waste [1]. If hospital waste is not properly managed and disposed of, it can result in injury by contaminated sharps and infection with Hepatitis B, C, and HIV [1]. Treatment of this huge amount of medical wastes cab be done via Incineration, Chemical Disinfection, Autoclaving, Encapsulation, or Microwave irradiation etc. for all of these methods, an automatic waste categorizing system plays a critical role.

Nowadays, developed countries such as Japan, Singapore, and Germany have implemented garbage collection and classification systems concentrating in the category after source separation [2]. In waste incineration facilities of Germany, electromagnetic separating devices for recycling metals are components. However, only metal waste are sorted automatically, the plastic trash, glass, etc. still rely on manual sorting which leads to consume huge manpower and awful work environments[2].

In this research a fuzzy rule-based system is introduced. Input of the system is a 2D RGB frame which is captured online and output of the system is an array showing certainty factor of belonging of each object of the frame to a waste type and a waste class. The considered classes and subclasses in this project include Microbiological Waste (Ampoules, PCR Tubes, Petridishes, Sample Tubes), Non-Recyclable (Ceramic Mugs, Feeding Bottles, Food Containers), Pathological Waste (Bandage Spool, Bottles, Cotton Balls, Gauze Pads), Pharmaceutical Waste (Inhalers, Medicine Bottles, Pipettes, Vials), Recyclable (Aerosol Cans, Forks, Juice Bottles, Mineral Water, Paper Cups), Sharps (Razor Blades, Scalpel Blades, Scalpels, Syringes). In order to classify the waste types, a fuzzy expert system is used including 24 rules and a number of fuzzy terms which are based on the extracted features from the input frame.

II. RELATED WORKS

Usually, the recycling process is focused on automatic sorting for massive plastics [5]. Massive plastics are mainly utilized to produce bottles, packaging and bags. Intelligent sorting systems, based on the image recognition and classification were developed **[3]** including (1) shape recognition **[4]**, (2) linear discriminate analysis (LDA) applying to gray level histograms on images **[5]**, (3) using physical properties such us density, and near infrared spectroscopy (NIR) **[6]**, and (4) difference of the transmittance (or absorption) between various kinds of plastics to an infrared InGaAsP laser **[7]**.

In some applications, e.g. medical image analysis, image information is not sufficient to extract the objects of interest, because the intensity difference among objects is not always distinctive. Hence, information about shape of objects should also be considered. Chen et al. **[8]** used the mean shape of the training set as a prior knowledge. Leventon et al. [9] derived shape parameters by PCA on a set of signed distance of training images. Then, segmentation was done under the influence of image force and shape parameters which were estimated by MAP. Tsai et al. [9] also represented the shape parameters by PCA.

Usually the segmentation methods use the level set method which assumes one object has only one region. In [11], the authors proposed the shape-based level set segmentation method for objects with 2 homogenous regions.

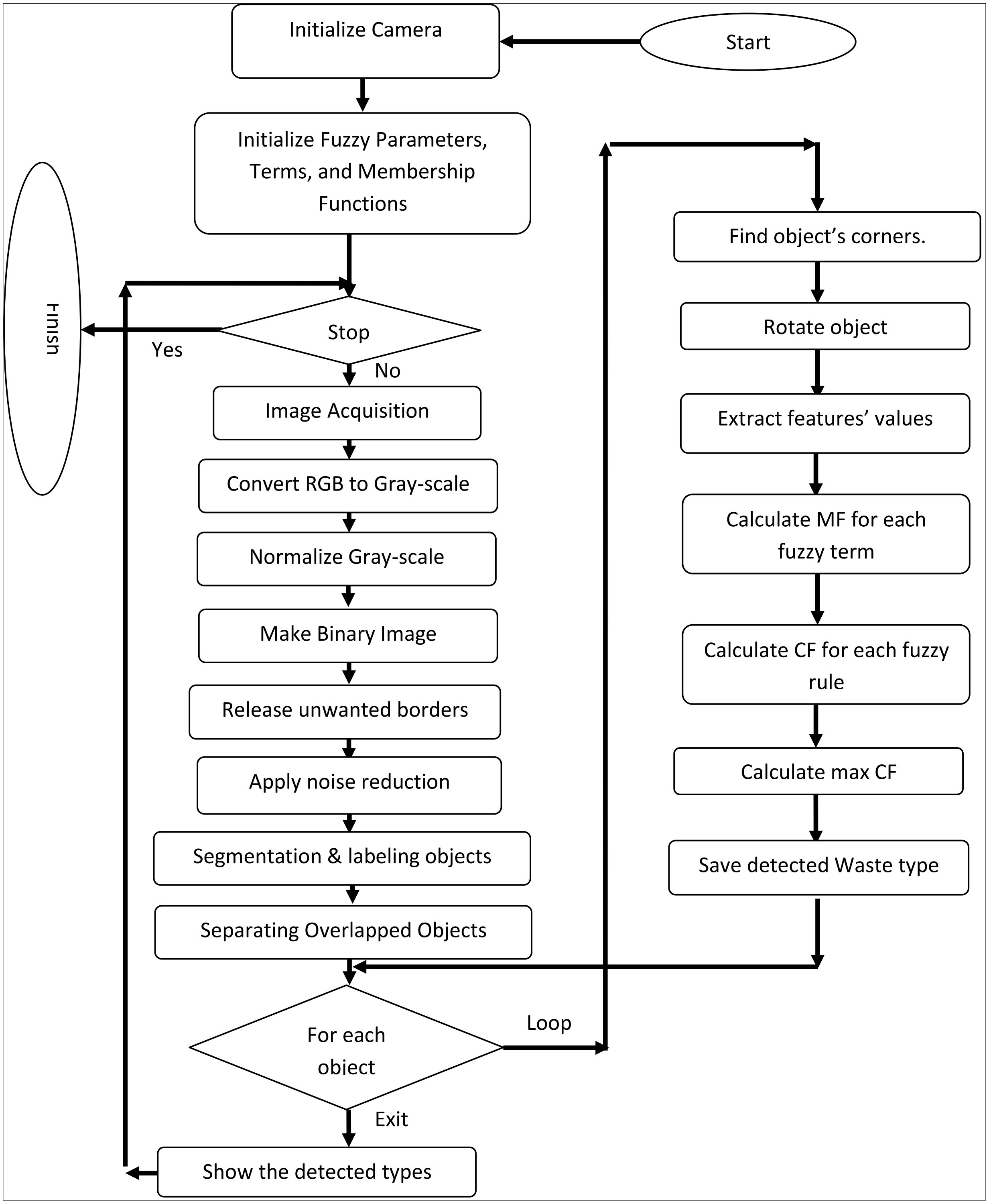

Figure 1. Fuzzy Waste Type Detection Flowchart

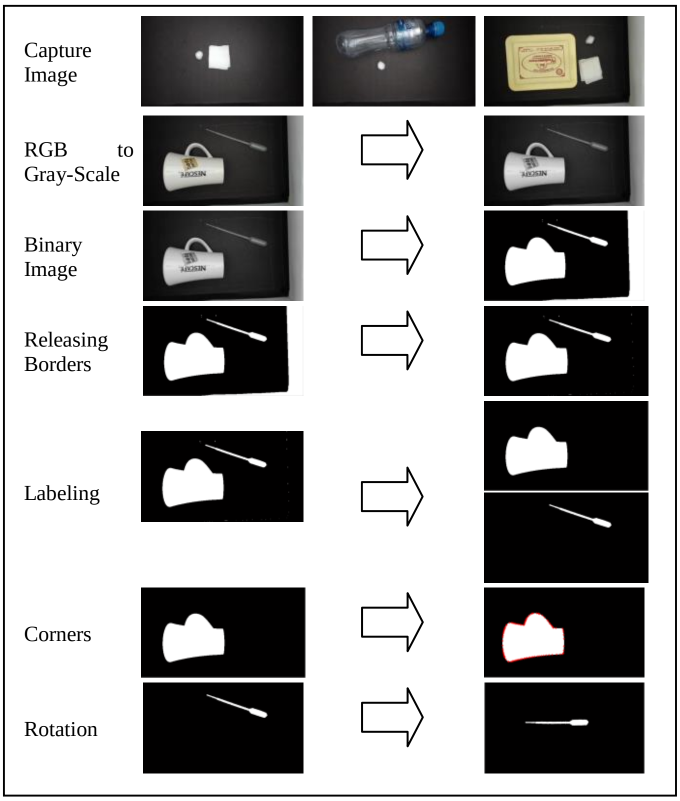

Figure 2. Some Applied Pre-processing Operations

Furthermore, a multi-resolution image representation approach is usually used to better analyze the information presenting in an image. Reference [12] used multi-resolution wavelet decomposition to reconstruct the original image. Then, an unsupervised neural network with fuzzy learning rules was used to segment the reconstructed image.

In [13] and for thermoplastics, a set of technologies were applied to the recovery of plastics wastes from electronic and automotive sectors. Also in [14], authors used a classifier based on the measurement of the temperature after heating the wastes using a laser diode.

The method introduced in **[2]** obtains waste images from the refuse conveyor belt using a high-speed camera system. Reference **[3]** proposes a method to label the different plastic resins using n fluorescent markers in a way such that unique spectral signatures are generated and thereby avoid the known drawbacks of existing plastic sorting methods.

Reference [15] presents an automated classification system for thermoplastics that can properly sort the most common automotive industry plastics. The core of this new automated system is that it fuses the information of three different sensors: a CCD of visible spectra, a NIR hyper-spectral sensor and inductive sensors. It is based on neural networks.

III. PROPOSED METHOD

Flowchart of the method followed in this research is shown in Figure 1. Generally this process is combined of two main steps; first some pre- processing operations are done on the image in order to enhance images quality, to separate objects, and to eliminate unwanted areas inside the image. In the rest of this section, after a brief view at the utilized fuzzy system, our method is described in detail.

A. *Fuzzy Expert System*

Fuzzy set theory provides a host of attractive aggregation connectives for integrating membership values representing uncertain information. The membership function of a fuzzy set in a functional form typically may be a bell-shaped function, triangle-shaped function, trapezoid-shaped function, etc.

In fuzzy systems, describing the control rules is usually simpler and easier, often requiring fewer rules, and thus the systems execute faster than conventional systems. Fuzzy systems often achieve tractability, robustness, and overall low cost.

The procedure for obtaining the fuzzy output of such a knowledge base can be formulated as follows [16].

- The firing level of the ith rule is determined by:

$$A_i(x_0) \times B_i(y_0) \tag{1}$$

- The output of the ith rule is calculated by:

$$C_i(w) = A_i(x_0) \times B_i(y_0) \rightarrow C_i(w) for\ all\ w \in W \tag{2}$$

- The overall system output, C, is obtained from the individual rule outputs C_i by:

$$C(w) = Agg\{C_1, \dots, C_n\}\ for\ all\ w \in W \tag{3}$$

B. *Waste Segregation Method*

Our segregation method is as follows:

1) *Capture image.*

2) *Apply some preprocessing operations. The operations and their effects were illustrated in Figure 2. These processes include:*

a) Normalizing RGB image and setting light coefficients.

In order to reduce the effect of different light conditions in the image capturing process, triple RBG elements are normalized. First the image is converted to the binary domain. The average of each R, G, and B element in the background pixels (In the binary image pixels which are detected as non-object pixels) is calculated, and the average of all background pixels is calculated. Finally based on the difference of each element average and the calculated total average, corresponding values are updated.

In some conditions and according to the light condition, range of intensity values of different pixels (including the ones belong to the various kinds of wastes and background) is too limited so that their separation is not possible. In order to solve this problem, this range should get widen. The correction is done in two steps. First when the final binary image is extracted. (Extraction binary image is one of the most critical steps. By this process, object areas in the image are separated from background pixels). Second when the classification is done and while intensity is used as a feature to detect waste type. In both steps according to the range of the average of the intensity values in the background and object Gray-scale pixels, a coefficient is defined and is applied to the corresponding intensity values.

b) Converting RGB image to Gray-Scale image.

c) Building binary image.

d) Releasing unwanted borders of the binary image.

Because of the inaccurate view of the camera, usually there is an unwanted light border in the captured image. This border should be removed before the classification. We do border removal by sweeping the image in each side. Each vertical and horizontal line whose pixels are detected as non-background pixels is removed from the image.

e) Applying noise reduction on the binary image.

f) Segmentation and labeling existing objects.

In this step, labeling operator is applied and objects are counted in the binary image. Then, small portions are ignored. To do so, number of pixels of that section is counted and is compared with a threshold value. Threshold is calculated based on the size of the corresponding image.

g) Separating overlapped objects.

After applying morphological operations on each object and separating different parts of the results, they are compared with an original binary image and the overlapped objects are separated.

h) Finding corners of objects.

i) Rotating each object to its horizontal position.

3) Extract proper features for each object from the corresponding captured image.

Classification is done based on the information achieved from the captured image. It is clear that all the extracted information cannot be considered for classification and a number of more informative are selected while the selected features or a combination of them are able to distinguish objects from each other. Since our classification is not a history based method, it only uses features which are extracted from current 2-D color captured frame. Therefore only the features are accountable which are extracted from spatial information of each pixel or each object of this image. From all features, geometric features such as length, width, ratio of length on width, diameter, object geometric shape, and so on are more effective. They are accountable because of their independency to the light and environment condition. RGB color information is less useful because of the light condition, proximity of camera and objects, and light effect on the color and intensity of captured object. HSI color model which is used in these kinds of projects is less useful in our project because of the above reasons.

Final considered features include:

- How much the object looks like a square?

$$S_i = min\left\{\frac{1-\delta_{h_i}}{l_i}, \frac{1-\delta_{l_i}}{h_i}\right\} \times \beta \tag{4}$$

where i stands to ith object. δ_{h_i} is standard deviation of height of different parts of object. δ_{l_i} is standard deviation of length of different parts of object. l_i and h_i refer to mean of the length and height of different parts of object. And, β is a coefficient which is set to 0.8 for small objects and 1 for big objects.

- How much the object looks like a circle?

$$\begin{aligned} C_i &= \frac{\left(\frac{1-Ci_r}{Ci_r+Ni_r}\right) + 2 \times Ratio_r}{3} \\ Ratio_r &= min\left\{\frac{1-|2\times r - h_i|}{2\times r}, \frac{1-|2\times r - l_i|}{2\times r}\right\} \end{aligned} \tag{5}$$

r increases step by step from zero up to the level that the number of pixels at radius r belonging to the object, Ci_r, is less than the pixels being not belonged, Ni_r.

- Ratio of max length on max height of the object.
- Ratio of max length on mode height of the object.
- Ratio of waste's length on its mode height (height with most frequent)
- Ratio of height of the object on height of the image.
- Ratio of length of the object on length of the image.
- How many degrees of having two lumps.
- Distance between two lumps on the object.
- HSI color model (Hue, Saturation, Intensity) and mean of each element all over the object.
- How much the object looks like a trapezium?
- How many degrees of having two height levels.
- How many degrees of having a hole inside the object.
- How much the object looks like white?

$$W_i = \frac{mean\{R,G,B\}}{mean(|\{R,G,B\} - mean\{R,G,B\}|)} \tag{6}$$

Where R, G, B refer to average value of Red, Green and Blue values respectively of all object pixels.

- Ratio of mean I (Intensity) on mean H (Hue).
- Size of the object.

4) Determine fuzzy parameters.

Extracted fuzzy parameters and corresponding fuzzy terms are listed in Table 1.

TABLE 1. FUZZY PARAMETERS AND THEIR FUZZY TERMS

Fuzzy Parameters	Fuzzy Terms
Ratio of max length on max height of the object.	Very Large, Large, Medium, Low
Ratio of max length on mode height of the object.	Large
Degree of having two lumps.	Two_Lumps
Size of the object.	Very Big, Big, Rather Big, Small
How much the object looks like a square?	Very High, High
How much the object looks like a trapezium?	High, Rather High
How much the object looks like a circle?	High, Medium, Low
Intensity on Hue.	Rather High, High
Hue.	Very High, High
Saturation.	Low, High
Mean value of white color.	High
Ratio of height of the object on height of the image.	High
Ratio of length of the object on length of the image.	High
Degree of having two height levels.	Medium, High

5) *Define fuzzy terms.*

6) *Initialize fuzzy membership functions' parameters.*

One of the most critical sections is the way that values are assigned to different parameters of the fuzzy membership functions. Considering to the nature of the used fuzzy terms in this project, three types of fuzzy membership function are used. Linear fuzzy membership function (Ascending and Descending), Triangular fuzzy membership function, and Trapezium fuzzy membership function. Linear FMFs have two parameters, Triangular FMFs have three parameters, and Trapezium FMFs have four parameters. In this project, values are assigned to the parameters experimentally.

7) *Define of fuzzy rules.*

Decision maker or classifier of the system is an expert system including a number of rules. The rules are designed based on the fuzzy terms and membership degree of each fuzzy parameter.

24 rules are designed for the system. It means for each waste type, a separate rule is designed. Each of these rules calculates the membership degree of a mentioned object in the corresponding class of the waste type. So the outputs of rules are 24 degree values. Finally the object is classified as a waste type with maximum value between all rules.

By using a more comprehensive rule more than a waste type can be classified. Using this method and by reducing the number of rules, speed of the system increases. The system did not follow this method so for each waste type a separate rule exists. This decision was made due to low importance of execution time in this project compared to its accuracy. In addition processing of 24 rules is not time consumer among expert system with tens of thousands of rules. Furthermore, extension of the system to classify more waste types in future is much easier.

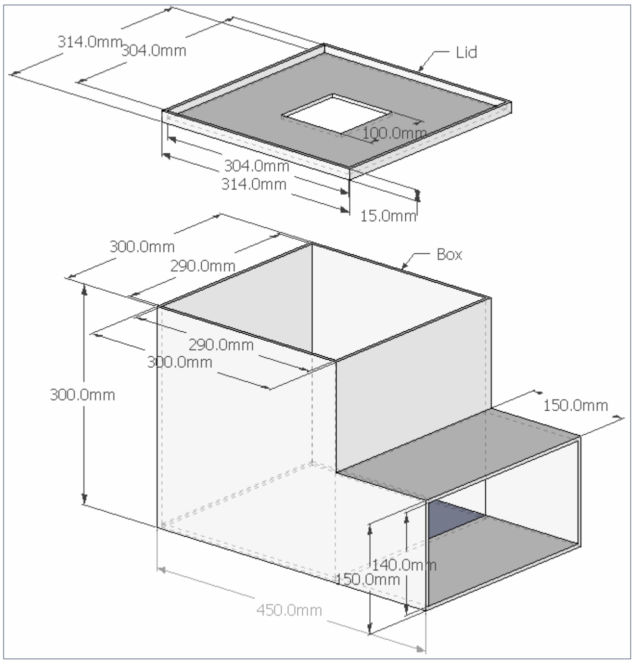

Figure 3. The Prepared Box

IV. EXPERIMENTS AND RESULTS

In order to evaluate performance of the proposed system, this was implemented using Matlab 2014. A box like what is shown in Figure 3 was built and a Logitech C920 camera was used. The tests were done online and using more than 500 waste samples including ones were new and the used wastes. The selection of wastes was done comprehensively so that from all waste types, in different light conditions, different positions, different waste colors, different sizes, and filled with different colorful liquids and in different positions and rotation degree existed in the test samples. The tests were done whether there was one object or more than one object in the scene.

A number of outputs of the system are presented in Figure 4. As it is clear in this figure, all the samples are classified correctly. In addition, Table II shows percentage of correct detection times for each waste type separately. In some items such as Mineral Water which its shape is very near to Feeding Bottles and Juice Bottles or Aerosol Cans which do not follow a specific shape format in different samples, the results are worse. Briefly average of the accuracy of the system is more than 94% which is acceptable.

V. DISCUSSION

Like all systems, the proposed system in this paper has some advantages and some drawbacks including:

- Technical Preferences and Advantages
  - High accuracy percentage of detection.
  - No limitation on the number of waste types; by adding a new rule, a new waste type is detectable.
  - Decision method is conceptual and understandable for human beings.
  - Unlike methods such as ANN, detection of a big number of waste types is possible.

TABLE II ACCURACY OF SYSTEM USING DIFFERENT WASTE TYPES

Waste Type	Accuracy	Waste Type	Accuracy
Ampoules	92%	PCR Tubes	87%
Petridishes	100%	Sample Tubes	85.5%
Ceramic Mugs	96.2%	Feeding Bottles	86.4%
Food Containers	100%	Bandage Spool	94%
Bottles	94.3%	Cotton Balls	97%
Gauze Pads	100%	Inhalers	96%
Medicine Bottles	94.3%	Pipettes	93.45%
Vials	95.4%	Aerosol Cans	88%
Forks	96.5%	Juice Bottles	87%
Mineral Water	87.5%	Paper Cups	91.5%
Razor Blades	100%	Scalpel Blades	97.2%
Scalpels	98.2%	Syringes	100%
Average		94.06%	

  - It is not required to provide training samples.
  - By using fuzzy concept, separation of similar objects is more meaningful.
  - Transparency of the system is high. It is possible to explain why and how a decision has been made.
- Technical Challenges and Risks
  - High number of effective parameters. (Each fuzzy membership function has at least two parameters.)
  - Adding a new type and a new rule effects on the others' performances.
  - Fuzzy parameters should be set manually.
  - The unmanageable effect of environmental conditions on the achieved accuracy.
  - Calculation of fuzzy membership values and sequential investigation of rules are time consuming.

VI. CONCLUSION

In this research, a fuzzy rule based waste segregation system was introduced. The main contribution of the system was classifying 24 predefined waste types from 8 medical waste classes. A large number of fuzzy terms were used in order to cover all similar states between these waste types and a fuzzy rule based system was used in order to calculate certainty factor of belonging each captured image object to one waste type. This system was run and tested on real environment and using real waste samples. The results show that on different light conditions, different view degree of camera and different positions of the objects, this system was capable to segregate objects.

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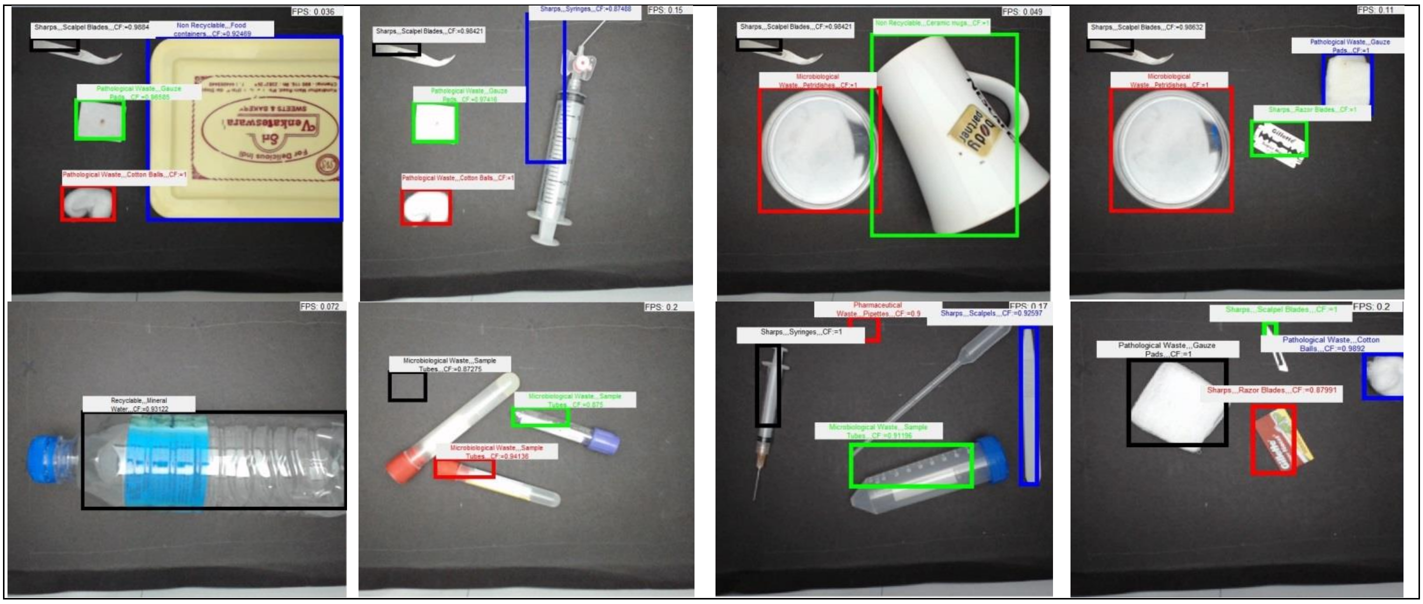

Figure 4 A Number of Segregation Results by the System