AUTOMATED RECYCLING ARM

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Abstract: The importance of waste recycling is no longer a secret to anyone. However, the recycling rate in the world is relatively low, people are not interested enough in this problem. This paper the prototype of an intelligent, autonomous system, using live object detection, capable of sorting waste, with a low price and good speed. The waste objects are identified by means of a neural network, implemented on a Raspberry Pi board. The robotic arm, which picks up and transports the detected object into the appropriate bin, is controlled by an Arduino Nano board. The prototype was tested for various types of waste and the encouraging results show that it can successfully be implemented at an industrial scale, as part of waste management solutions.

Keywords: *recycling, robotic arm, waste, object detection*

I. INTRODUCTION

Environmental pollution began to make its presence felt with the start of the industrial revolution in the nineteenth century and has continued to grow since then, becoming a real public health problem today. Plastic contamination in oceans and inland waters is a serious issue that affects not only the aquatic environment but also people. Plastics contiguities between 60%-80% of the waste present in the marine environment and 90% of the waste floating in seas and oceans. Statistics show that at least 267 species worldwide are affected by this problem.

Around the world, recycling rates are widely reported – but different measurement methods make comparisons difficult; eye-catching recycling rate claims need to be treated with caution. In July 2018, China announced its plans to ban the import of over 24 varieties of solid waste, including plastic and unsorted paper. The ban takes effect from September 2018. So, with the Chinese door closing on foreign waste, what are the plans for countries currently exporting their waste there? Several countries, including the UK, are now considering imposing taxes on plastic items to help reduce usage and encourage recycling. In Australia, 51% of the household waste gets recycled, on par with northern European countries, and exceeding the average recycling rate of 42% of the 28 countries in the EU. When one considers the unique geography and dispersed population of Australia, this is seen as quite an achievement [1]. Romania ranks second to last in the Europe Union in terms of waste recycling rate, at only 14%, according to an infographic by Social Monitor. Only Malta recycles a lower percentage of all municipal waste generated (6%). The European Union has set a target of 2020 for each country to recycle at least 50% of the waste produced by its municipalities. In recent years, the amount of non-recycled waste reached unprecedented levels, with Romania producing 4.58 million tons of non-recycled municipal waste per year, or 12.500 tons per day [2].

Waste collection is one of the targets of smart cities. It is a daily task in urban areas, and it entails the planning of waste truck routes, considering environmental, economic, and social factors. An optimal path planning algorithm together with a practical software platform for smart and sustainable cities is presented in [3]; the system computes the optimal waste collection routes, minimizing the impact on the environment.

Object detection is a computer vision technique that works to detect and locate objects within a video or image. Object detection draws borders around these detected objects, which allow us to locate where said objects are, in a given picture or a scene in a video. Another similar computer vision technique is object detection, which is inextricably linked to other similar computer vision techniques like image recognition and image segmentation. But there are important differences, image recognition only outputs a class label for an identified object, and image segmentation creates a pixel-level understanding of a scene's elements. What separate object detection from these other tasks is its unique ability to locate objects within an image or video and then framing them in frames. This allows us to track and then count those objects. Object detection can be broken down into machine learning-based approaches and deep learning – based approaches [4].

One of top scientific trends today is to simulate the human brain behavior, in particular, deep learning strategies pave the way towards many new applications, thanks to their ability to manage complex architectures. The development of deep learning has led to a dramatic increase in the number of applications of artificial intelligence in many categories. However, the training of deeper neural networks for stable and accurate models translates into artificial neural networks (ANNs) that become unmanageable as the number of features increases [5].

Image recognition represents a set of methods for detecting and analyzing images to enable the automation of a specific task. It is a technology that is capable of identifying places, people, objects and many other types of elements within an image, and drawing conclusions from them by analyzing them, but it is not capable to generate the position of the object. With an image recognition or object detection system or platform, it is possible to automate

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many business processes and thus improve productivity. Indeed, once a model recognizes an element on an image or video, it can be programmed to perform a particular action. These systems are already used in many industries and sectors. For example, in the telecommunications sector, a quality control automation solution was deployed. In fact, field technicians use an image recognition system to control the quality of their installations [6].

II. THEME AND OBJECTIVES

The problem with waste recycling and collection centers is that significant financial and human resources are spent to manage this waste. The low speed with which objects are sorted is yet another inconvenience.

The paper proposes an intelligent and autonomous system, which can provide a sorting of waste with high accuracy (more than 80%), using neural networks to achieve the detection of objects. The process is low cost, favoring the adoption of the system worldwide. This mechanism can be placed on a conveyor belt on which different types of waste are present. The system is capable to recognize each type of waste and place it in the appropriate container. Surgical masks, which have become a major problem in the context of the pandemic, can also be identified.

The main objective of this project is to create a miniature scale mechanism, able to identify objects made of different materials, and then to sort them automatically.

Another objective is to obtain a better recognition rate, being able to recognize objects in different positions or different brightness level, but also to recognize several different objects from the same category.

The steps are: implement a neural network on the Raspberry Pi, training with as many different images of the objects they are going to recognize and create a robotic arm to grab and move objects in the appropriate waste bin compartments. The robotic arm is mobile on several axes and strong enough so that it can handle used objects. The project uses: a Raspberry Pi 4 board, a camera, an Arduino Nano board, a step-by-step motor and 4 servomotors.

III. FEATURES AND SPECIFICATIONS

The diagram in Fig. 1. shows how the object detection process works. Based on the captured image, the object detection algorithm determines whether the detected object is paper, plastic, face mask, battery or glass and its position.

The system combines hardware and software components. The hardware components can be separated into two parts: the central unit, which deals with object detection, and the object movement system (Fig. 2). The central unit consists of the Raspberry Pi board and the camera, while the displacement system is actually the Arduino Nano board, which controls the 4 servomotors, they make up the robotic arm and a step-by-step motor, which ensures the horizontal movement of assembly.

The main software part is represented by the neural network, through which the detection and object sorting is performed. TensorFlow Lite was used to implement a neuronal network on the Raspberry Pi. TensorFlow Lite is a set of tools that enables on-device machine learning by helping developers run their models on mobile, embedded and IoT devices. A TensorFlow Lite model is represented in a special efficient portable format. This provides several advantages over TensorFlow's protocol buffer model format such as reduced size and faster inference that enables TensorFlow Lite to execute efficiently on devices with limited compute and memory resources [6]. TensorFlow Lite is used for mobile devices, like Raspberry Pi, Single Shot Detector (SSD) model. SSD is a method for detecting objects in images using a single deep neural network, it computes both the location and class scores using small convolution filters. After extracting the feature maps, SSD applies 3x3 convolution filters for each cell to make prediction. For this project, Google Cloud AutoML was used to create a custom *tflite* model. Google AutoMl is a machine learning model builder for image recognition and object detection, offered as a service from Google Cloud.

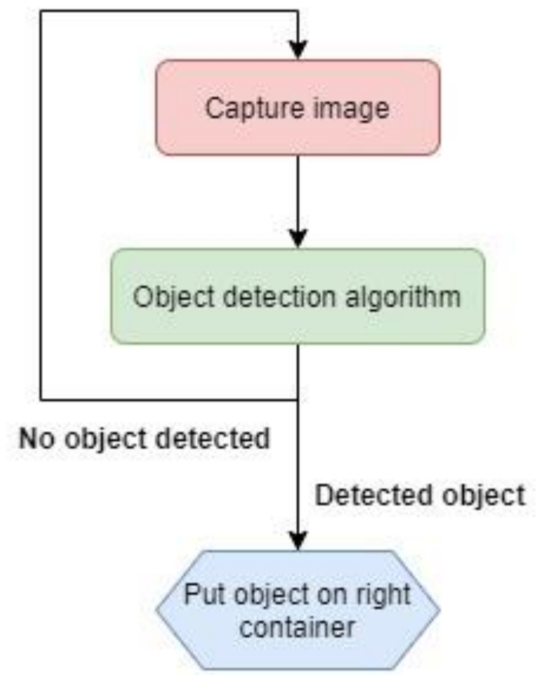

Figure 1. Flowchart of the object detection process.

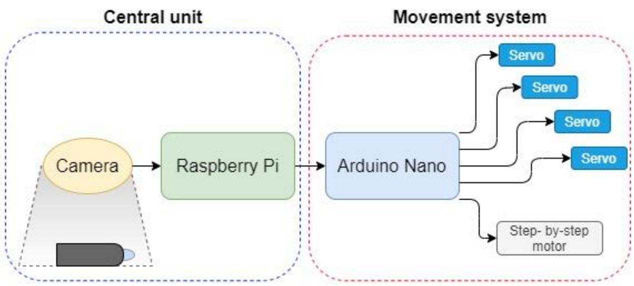

Figure 2. Hardware diagram.

AutoML Vision's machine learning code allows virtually anyone the tagged images required to train a system that is learning computer vision, enabling it to perform categorization and other image recognition and object recognition task.

To train the object detection model that can detect and recognize different materials, a new dataset has been created which includes 1738 images: 345 paper, 330 plastic, 316 face mask, 369 battery, 380 glass. To create these images, several objects from the same category were used to create as diverse a variety of objects as possible. Because the resolution of the phone camera is better than Raspberry Pi camera resolution, both cameras were used. This way, it was possible to easily change the camera used for detection to a higher resolution camera in the future, without affecting the accuracy of the system. At the same time, the algorithm is faster with lower resolution images.

The images were captured at various times of the day and a light source positioned in different places was added in certain frames. The algorithm is designed to work correctly, regardless of the orientation of light beams, the presence of light sources nearby or the position of the object in the frame.

To obtain a set of images as diverse and large as possible, a Matlab script was developed and used, through which the saturation of each image is automatically changed. The Matlab script applies changes in the orientation of the image, thus significantly multiplying the initial images, obtaining brighter images, but also darker ones. Several possible cases have been covered, some that may be encountered more often or some extreme ones, due to very low or very high brightness or due to high humidity in the air, which could change the transparency of the camera lens, slightly increasing the opacity level.

For the whole process to run as smoothly and easily as possible, the program takes the position from one file on its own and then saves them in another. This was followed by a manual check to remove blurry or useless images due to excessive contrast blur. The maximum image size is 1.5MB and 1024 pixels by 1024 pixels is suggested maximum. The number of samples per class of objects is recommended to be approximately equal. Minor imbalances do not generally create issues, but larger discrepancies between classes may lead to poor accuracy. After obtaining the training image, it must be labeled with the name of the category to which the object belongs. Only after labeling, the images are ready to be used for neural network training. The major advantage of using Google Cloud AutoML is that no high computing power is required on one's local device. However, the time required to train the model was about 13 hours. After that, two files were generated, one with the extension "*.tflite*" and another "*.txt*", the latter containing the names of the categories that include the objects used for training, categories that include the objects to be sorted.

The detection process proceeds as follows: an image is captured, based on which the detection algorithm determines whether the objects is similar to the ones the system was trained with; after establishing a verdict, if the object was recognized, the coordinates are generated (position and border around the object). The type of the object and the percentage of similarity are displayed, as well as the number of frames per second (Figure 3).

After analyzing the object and processing the data, a specific message is transmitted through serial communication to the Arduino Nano board. The message is represented by a number, with a single digit, specific for each category of objects; it is transmitted as an ASCII character and is transformed into a number in the program implemented on the Arduino board. This method was chosen because it is a fast way to transmit data through serial communication, so the whole sorting process is not delayed by this communication between Raspberry Pi and Arduino Nano. Although is does not transmit a long message, the transmission rate is quite high, so the Arduino board buffer requires periodic cleaning for the more accurate operation.

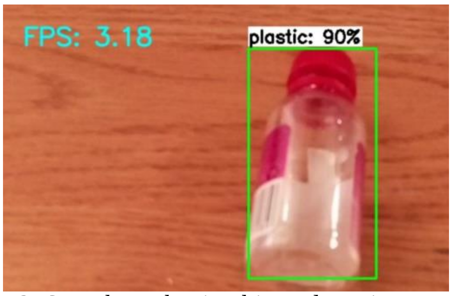

Figure 3. Sample – plastic object, detection rate 90%.

The Arduino board controls the robotic arm, which consists of 4 servo motors: two bigger ones (MG946R), positioned at the base and two smaller ones (SG90), located at the end, because they are lighter. 3 servo motors are used to make the mechanism mobile on all 3 axes and the fourth motor is used to grab the object. Each major operation performed by the 4 servomotors, both lifting and placing the object, consists of 11 movements. Light objects were chosen to avoid forcing the servomotors or dropping the object during movement. The force with each object is tight, varies depending on its size, for example, batteries, having smaller dimension, are tightened at a larger angle than a plastic or glass object, and a paper object or a surgical mask is grabbed with a greater force than other objects. Taking this aspect into account and creating scenarios for each situation avoids unnecessary strain and therefore premature damage to the servo motor responsible for tightening the object. The object clamping mechanism, attached to the servomotor at the end of the arm, has been modified so that difficulties in gripping and holding cylindrical objects are avoided, even in the case of glossy objects. The physical connection of the servo motors is made by means of cut aluminum plates and screws, to make it easier and cheaper to change certain parts, so that the assembly is as light as possible, but at the same time the system is rigid enough.

A step-by-step motor (35h20hm), powered by 14 V, is used to achieve the horizontal axis movement. The complete system (Figure 4), except for the Raspberry Pi board, is powered by a 14 V and 1.5 A voltage source and a Step-Down DC module was used for the 5 V supply. The time required to move the object from the recognition point to the end point is about 25 seconds and after moving the object, the arm returns to its original position, waiting for a new object to be identified.

IV. RESULTS

Tests performed on samples of several objects revealed that the detection accuracy for each object is quite good, being over 85%. It has been observed that in some frames it is difficult to identify batteries, and a lower detection accuracy was observed. The most accurately identified type of waste is is plastic.

The secondary mechanism manages to hold the object steady while moving, no problems were observed in the process of gripping and moving the object. The object is grabbed tightly enough; no problems were observed in the case of glossy objects.

The heaviest objects are made of glass, but the assembly does not encounter difficulties in lifting and moving them. For now, the mechanism can grab objects that are in a certain position, an aspect that needs future improvement, so that objects can be lifted from any position. Because such a system would be used together with a conveyor belt, arranging items in a certain position prior to sorting would entail extra cost as well as an extra risk of failure. Especially considering the advantage of using object detection, which provides the 2D coordinates of the object in space, so the object does not always have to be in the same position and at the same point to be recognized and taken.

The object detection algorithm was trained with images containing objects in different positions, such as oblique or horizontal, so it has no difficulty in recognizing objects that are in positions other than vertical. The accuracy in these cases is very close or even higher when the object is in a vertical position (Figure 5).

Tests were also performed with objects different from those with which the model was trained but made of the same category of material. It was found that the algorithm works well even with new objects, managing to identify them with a high accuracy rate (78%-88%), but less accurate than in the case of familiar objects.

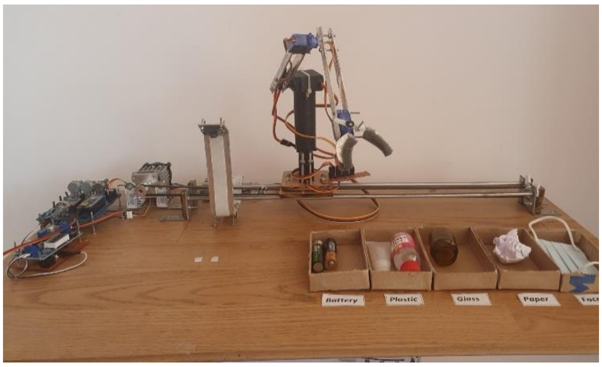

Figure 4. The complete system.

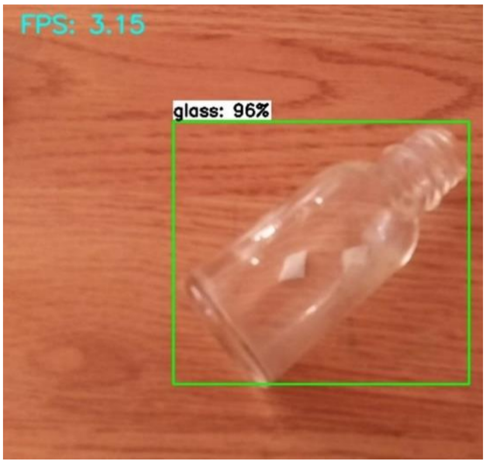

Figure 5. Detection of object in oblique position.

V. CONCLUSIONS

In its current form, the proposed recycling system is too slow to be commercially viable. For a prototype, however, a very good speed was obtained, the whole recycling process for an object is realized in less than one minute, with a precision over 85% and works well with new objects. Implementing this project would reduce the effort for employees to manually sort items on the conveyor belt, as well as reduce the financial and human resources needed to manage this waste, while increasing the speed of sorting.

The fact that it does not require human assistance and can operate 24/7 without interruption is a great advantage. A considerable advantage is that the objects do not need to be pre-sorted or arranged in a certain way, so that they can be detected, as in the case of conventional systems. Another advantage compared to the systems currently used is the adaptability, because other objects can easily and cheaply be added that need to be sorted. A very good example are the surgical masks, whose use rate has increased drastically due to the SARS-CoV-2 pandemic, these masks being harmful to the environment due to the large amount of plastic they contain. After minor modifications, so that the process is also based on the coordinates at which the object is in the frame, as well as the ability of the arm to take the objects in any position, the efficiency and adaptability of this system will increase considerably. However, a commercial version requires more processing power than the Raspberry Pi could provide. Given that the algorithm was implemented on a minicomputer, such as the Raspberry Pi, which has limited computing power, but also the fact that the aim was to create a prototype using the lowest possible cost, the obtained accuracy and speed outweigh the occasional errors or difficulties in detecting objects.

This prototype is a step forward towards a better future, one in which recycling rates increase substantially; such a mechanism would not only help poor areas, where recycling is an abstract thing, but also large cities, where the selective collection rate is higher, but not nearly high enough.

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