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PiVisionSort: Integrating Image Processing and Machine Learning for Material Recognition on Conveyor Belts

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Abstract. This research aims to develop an advanced material detection system for conveyor belts, utilizing state-of-the-art image processing and machine learning techniques to automate the identification of various materials, thereby enhancing operational efficiency and accuracy in industrial settings. Current methods in material detection, such as traditional manual sorting and basic automated systems, often need more precision and adaptability in dynamic industrial environments. This paper identifies a gap in the practical and reliable detection of diverse materials under varying environmental conditions. The primary research questions addressed include: How can modern image processing and machine learning techniques improve material detection accuracy? What optimizations can be applied to ensure real-time processing efficiency? The proposed solution integrates a strategic camera setup with controlled lighting, robust image preprocessing algorithms (noise reduction, normalization, and resizing), and custom-designed detection algorithms using machine learning models. This system outperforms existing solutions by offering higher detection accuracy and adaptability to diverse industrial conditions. An interface is developed to display detection results and provide intuitive controls for system adjustments, ensuring practical use by industrial professionals. Rigorous testing and validation processes are implemented to enhance detection accuracy and processing speeds, with specific performance metrics established to measure efficacy. This paper provides a transformative impact on the manufacturing and processing industries by addressing environmental variability and material diversity.

Keywords. Image Processing; Machine Learning Techniques; Automated material identification; Precision in material detection.

1. Introduction

In the rapidly advancing world of industrial automation, the recycling industry is a critical sector where efficiency and precision in material sorting are paramount. As environ-

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mental concerns and resource sustainability become increasingly pressing, the need for effective recycling methods, especially in metal sorting from waste. This paper shows a solution to enhance the metal detection and recognition process on conveyor belts, particularly within the challenging environment of an eddy current machine used in recycling operations. Our primary objective is to enhance the machine's efficiency, ensuring its continuous operation around the clock. We achieved this by integrating a sophisticated Raspberry Pi-based system equipped with a camera and strategically placed LED lights to monitor the conveyor belt. The system's design allows for real-time detection of material presence, a critical factor in streamlining the sorting process. The task unfolds in two distinct yet interrelated parts. Initially, we focused on detecting material presence, employing a simple yet effective red and green LED light system. These lights indicate the absence or presence of materials, providing immediate and clear communication to the human operators overseeing the process. The second part of our work took a more nuanced turn, concentrating on the identification and enumeration of metal pieces in motion. A vital aspect of this phase distinguishes between various metals, such as copper, aluminium, and brass, utilizing colour recognition technology. This method proved exceptionally practical, demonstrating a remarkable 93 percent accuracy in identifying metals based on their colour signatures.

This paper outlines the comprehensive methodology, algorithms, and machine-learning techniques we used to achieve our goals. Our findings and the system we developed demonstrate the potential for significant improvements in metal separation processes and set a new benchmark for accuracy and efficiency in industrial material handling.

1.1. Background

As it has been demonstrated in Fig. 1 the eddy current separator is a machine for separating nonferrous metals from other materials. For example, alloys such as aluminium and copper are recycled and entered into the reuse cycle. This technology works on the principle of magnetic separation, where nonferrous metals are affected by a magnetic field and change their orientation due to their electrical properties. The primary and basic design of eddy current separator machines includes a conveyor belt that passes the material over itself, and there is a drum at the end of the belt in the lower part that does the actual separation [1].

1.2. Problem

The existing challenges in metal granule separation in industries include the dusty and unhealthy working environment, potential for human error due to fatigue, and difficulties in further separating granules with similar weight but different colours. Moreover, the current separation machines are expensive and may not effectively detect different grayscale colours, limiting their accuracy and efficiency.

1.3. Existing Body of Knowledge and State of the Art

In [2,3], They developed an optical sorting system that uses cameras and sensors to detect differences in the materials' colour, size, and shape. While these systems are suitable for simple sorting tasks, they need help with overlapping materials. Other researchers [4,5,6]

Figure 1. Eddy Current Separator Machine

are working with X-ray imaging, which is quite expensive, making it less viable for widespread use. Meanwhile, others [7] work with near-infrared spectroscopy; this technique identifies chemical compositions but always requires precise calibration, limiting its application on fast-moving conveyor belts. Other researchers are exploring electromagnetic methods with various applications, such as finding shallow metal objects, utility detection, and avoiding buried metals in construction sites. These devices can feature different coil configurations and may use sophisticated software to provide detailed data like the depth of detected objects. The effectiveness of a metal detector is influenced by the target's surface area and depth, with optimal detection occurring for larger, shallower objects. Detection depths generally reach up to 15 meters [8,9].

In [10], the authors are investigating and improving aluminum recycling processes from waste. They specifically address the problems associated with impurities in recycled aluminum, including elements such as silicon, iron, copper, and other metals. These impurities can reduce the quality of recycled aluminum and complicate the recycling process. The paper examines various methods for separating and purifying aluminum, including magnetic separation, airflow separation, and more advanced technologies, such as using lasers to separate different elements, which are at the forefront of recycling innovation. This study also focuses on different technologies to increase the purity of aluminium waste. It introduces methods such as dilution with raw materials to reduce the number of impurities in the final product. However, this method can negatively impact the recycling rate as it requires more material and can produce lower-value aluminium.

We also find recent research [11] on deep learning for nonferrous metal recognition, focusing on identifying and separating nonferrous metals from small scrap parts using deep learning technologies like the YOLO.v3 model and transfer learning to achieve high accuracy and speed in metal detection. However, running such models costs relatively high due to the need for specific hardware with good GPU capabilities. Other researchers are performing similar tasks using artificial intelligence techniques for enhanced sorting. They combine laser refraction spectroscopy and machine vision to improve aluminium scrap separation by integrating image and spectral data. However, like the previous study, these methods also require potent GPUs to run complex models. However, researchers perform similar tasks [12] with artificial intelligence techniques for enhanced sorting. They combine laser refraction spectroscopy and machine vision to improve aluminium scrap separation by integrating image and spectral data. However, like the previous studies [11], these methods also require potent GPUs to run complex models.

In the latest paper [13], recent research classifies aluminium using LIBS and artificial neural networks, focusing on separating aluminium alloys in car recycling. A laser creates a plasma on the sample's surface, and the resulting optical spectrum determines the elemental composition. However, this research focuses only on aluminium alloys rather than other metals, which we include in our current research. Additionally, relying solely on sensors in industrial workplaces is not wise since sensors in dusty and noisy environments might not provide accurate results, and all their experiments are conducted in laboratories [13].

A review of existing literature on metal recycling identifies a significant gap due to the need for more technologies suitable for industrial applications. Most research in metal detection conducts their tests in laboratory conditions [13]. These methods work well in controlled environments but may need to perform more adequately in industrial settings with dust and noise. Incomplete outputs can directly affect the accuracy of AI models, leading to decreased quality in decision-making. Additionally, running such models incurs higher costs due to the need for better hardware. In the present project, while being cost-effective, we solve the problem using the simplest machine learning algorithms. The cameras are not affected by industrial environments that include dust and noise, with no negative change observed in the camera's output. We proceed with straightforward image processing algorithms that do not require expensive hardware and are easy to assemble and disassemble, requiring less space and being portable. The focus is simplicity, portability, good speed, and reliable output. For this reason, we use an industrial camera, and the project is based on Raspberry Pi.

1.4. Research Questions

RQ: How can integrating advanced image processing and machine learning techniques enhance material detection on conveyor belts to improve operational efficiency and accuracy in industrial settings?

RQ1: What improvements are seen in the interpretability and reliability of material classification with the use of specific modern methods compared to traditional image processing techniques?

RQ2: What optimizations can be applied to specific clustering techniques to effectively preprocess images for real-time material segmentation on moving conveyor belts?

RQ3: What reductions in overall system costs and complexity can be achieved by combining machine learning techniques in industrial applications?

2. Supplementary Literature and Related Work

As researchers, engineers, and professionals in the recycling and waste management industry, your contributions are vital to the advancement of recycling technology. Various technologies are currently being explored to enhance the efficiency and accuracy of sorting processes in material detection and recycling. This section reviews the advancements and research contributions in this field, including your valuable work, in more detail. The Eddy Current Separator (ECS) [1] is a cornerstone in the recycling industry. It is designed to separate nonferrous metals like aluminium and copper from other materials through magnetic forces generated by alternating electric currents in a rotating drum. The drum, rotating at up to 2000 revolutions per minute, influences the direction of nonferrous metals on the conveyor belt, separating them from plastics, wood, and glass. One of the primary challenges with ECS machines is balancing processing speed and separation accuracy. The machine often operates 24/7 to handle several tons of material, requiring significant electricity. Maximizing speed can compromise separation quality, while slowing down the machine is impractical due to increased energy consumption. Our project aims to optimize this balance, enhancing efficiency and quality of separation while conserving resources and ensuring continuous operation. We employ machine vision technology to enable the ECS to monitor itself. Cameras and motion detection sensors are installed to track the presence and absence of materials on the conveyor belt. This technology ensures that the machine only operates when necessary, reducing energy waste and improving separation accuracy. This approach conserves electricity and enhances the purity of recycled metals, reducing the need for new raw materials and significantly minimizing environmental impact. Implementing machine vision allows the ECS to detect and process materials more accurately, preventing errors and improving the overall recycling quality, thereby contributing to a healthier environment.

Several studies in the field of metal recycling focuses on enhancing the processes and improving the detection of nonferrous metals such as aluminum and copper. Most research emphasizes the recycling of aluminum due to it's widespread use and economic value. In [14] they discuss the improvement of aluminum recycling by separating crushed aluminum, particularly the "twitch" type, which combines cast and forged aluminum. Magnetic Induction Spectroscopy (MIS) is used to classify and separate these types of aluminum. Laboratory results showed a recovery of 89.66 percent and a purity of 94.96 percent. However, industrial applications revealed performance degradation due to sensor misclassification, surface orientation, and the choice of machine learning algorithms. However, in [15] they review technologies for separating impurities to improve recycled aluminum quality. Pre-melting technologies, such as magnetic separation and eddy current separation, were evaluated. Eddy current separation, which uses powerful neodymium magnets, effectively separates nonferrous metals from waste. However, challenges such as shape and size irregularities, nonmetallic material separation, and equipment maintenance costs affect its overall efficiency. In [16] deep learning techniques, particularly YOLOv3, have been applied to identify and separate nonferrous metals from scrap cars. These methods demonstrated high accuracy (95.3 percent for aluminum and 91.4 percent for copper) but faced limitations in industrial scalability and hardware resource requirements. More straightforward algorithms like K-means and decision trees were suggested as cost-effective alternatives that can run on microcontrollers like Raspberry Pi. In [17] Christopher DiPaola's thesis develops an automatic classification system for nonferrous metals using infrared sensors and solenoid valves with compressed air. While, successful in laboratory settings, the system's reliability in industrial environments is questioned due to dust, noise, and sensor contamination issues. The need for robust hardware and cost-effective solutions remains a critical challenge. The [18] SHREDDERSORT research focused on sorting nonferrous metals from car waste using Laser Induced Breakdown Spectroscopy (LIBS) and artificial neural networks (ANNs). Despite its high accuracy in laboratory conditions, the LIBS technique struggled with sensitivity issues and contamination in industrial environments. The complexity and cost of AI models further limit their industrial application. While significant advancements have been made in metal recycling technologies, challenges such as industrial scalability, cost, and environmental conditions persist. Our project aims to address these issues by integrating machine vision and simpler, more efficient algorithms to optimize metal detection and separation in industrial settings.

3. Machine Learning and Image Processing Technologies

This research develops an intelligent system to detect and separate materials like aluminium, copper, and brass from a moving conveyor belt. The goal is to enhance the efficiency and accuracy of metal recycling at a lower cost, ensuring better purity of recycled metals. Advanced machine vision and image processing technologies improve the separation process. Cameras and sensors installed on the conveyor belt detect materials more accurately, making separation more efficient. This study addresses the growing need for more effective recycling technologies, especially as electronic and industrial waste production increases. Fig. 2 shows the actual material for which research is being conducted. A few kilograms of aluminium, copper, and messing metal in different shapes and sizes under 10 mm.

Figure 2. [1]:Aluminum, [2]:Copper, [3]:Messing

The use of machine learning algorithms [19,20,21] such as k-means and decision trees in this work enables more accurate interpretation and more reliable identification of materials. Compare to traditional methods that depend more on manual calculations, these modern techniques can analyze data more profoundly and accurately. This is especially important in industrial conditions where data influences by environmental factors and need fast reactions. The results of these methods are highly reliable and help to make more effective decisions in recycling processes. The methods used are OpenCV [22], followed by the K-means algorithm for clustering purpose, the decision tree to improve the accuracy of the diagnosis. OpenCV plays a key role in the development of the system as a robust library of image processing and machine vision. This library provides extensive capabilities for real-time image analysis and processing, including motion detection, texture analysis, material counting, and material-specific feature detection. It groups image data based on similar features. In Fig. 3 has been shown how K-means clustering works.

The decision tree algorithm improves decision-making by analyzing features extracted from images. It identifies material types based on logical rules, enhancing accuracy and interpretability. Combining image processing and machine learning allows for fast and efficient material recognition and separation. OpenCV facilitates the implementation of these algorithms in both lab and industrial settings. These methods offer a cost-effective alternative to traditional manual separation processes, reducing the workforce needed and improving safety while optimizing efficiency.

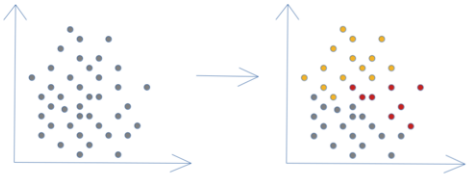

Figure 3. Clustering using k-means

4. Optimization with Decision tree

The K-means algorithm struggles with accuracy, especially when metals have mixed colours, like copper and brass, due to compression. Dust and changing lighting also complicate detection. A decision tree improves accuracy by analyzing colour percentages, optimizing the detection process and enhancing metal identification and separation. In Fig. 4, we see a metal mix of copper and messing among the samples checked for errors. The Gini index evaluates dataset splits by measuring inequality. It is calculated by

Figure 4. Messing detected as copper

subtracting the sum of the squared probabilities of each class from one. There are four classes in this case: three metals and one background. Higher Gini values indicate more inequality or heterogeneity in the dataset, and the index is used for binary splits in categorical target variables. [23,24].

$$Gini = 1 - \sum_{i=1}^{c} (P_i)^2 \tag{1}$$

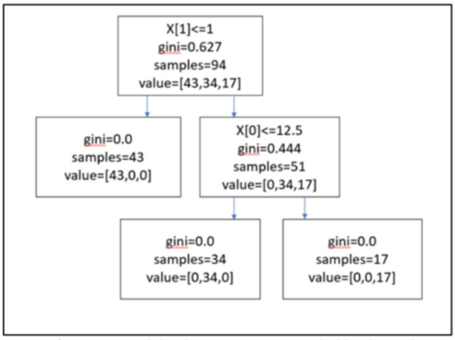

Figure 5. Structure of the decision-tree

Fig. 5 depicts our decision-tree diagram; we assume we should check aluminium first and then recheck the rest between copper and messing metals. The decision tree demonstrates an impressive model score of 1.0 based on binary splits of being accepted or rejected. This high score indicates that the three variables are weighted in varying ways and resulted in one score, showcasing the adaptability of the algorithm.

Fig. 6 shows the leading architecture of the algorithm. Initially, the camera captures images. It then determines whether there is an object in the image. If no object is detected, nothing will be displayed. If an object is detected, the image will be processed.

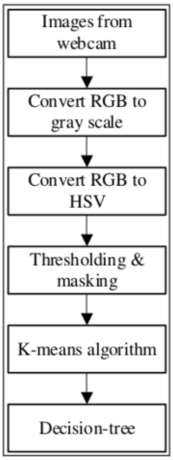

Figure 6. Algorithm process chart

The first step is converting the RGB image to grayscale. RGB represents colour with three values (red, green, blue), but only one colour channel is needed since the focus is on recognizing a single metal's colour. This simplifies the 3D RGB data into a 1D grayscale

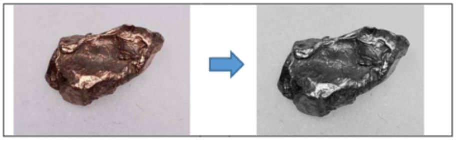

Figure 7. RGB to Gray scale

value, reducing complexity while capturing the necessary information which the Fig. 7 shows.

As we see in Fig. 8, the next step is converting the RGB image to the HSV colour space (hue, saturation, value), as HSV better separates colour information than RGB. This makes it easier to distinguish colours accurately, which is essential for the system's image-processing tasks.

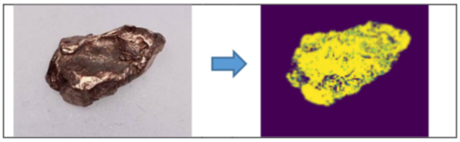

Figure 8. RGB to HSV

Fig. 9, is showing the thresholding which is a segmentation technique that simplifies image analysis by converting a grayscale image into a binary image. It helps focus on the essential areas by selecting target regions and ignoring irrelevant parts of the image, making colour and content analysis more straightforward.

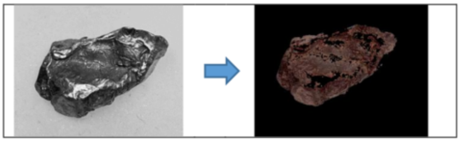

Figure 9. Thresholding

Fig. 10 is doing the masking, which, in image processing, involves isolating a small portion of an image to modify or analyze it while leaving the rest untouched. It helps with edge detection, noise reduction, and background removal. This technique benefits moving objects, allowing parameter adjustments for better results.

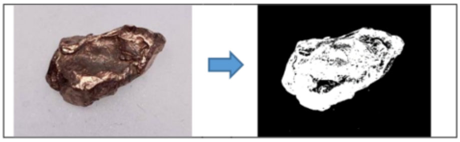

Figure 10. Masking

5. Evaluation

The developed system ensures its reliability and performance in real-world conditions through rigorous testing and validation. This phase involves testing and analyzing multiple scenarios to confirm that our solutions meet the required industrial standards and operational demands.

5.1. Prototyping and System Cost

The system has several key components: a Raspberry Pi, an ELP camera, an infrared light barrier sensor, and a set of red and green LED lamps. The approximate total cost for the setup is around 130 euro, making it a cost-effective solution compared to other industrial detection systems. The LED lamps are crucial in the notification system, providing visual cues for various states. This box, containing the Raspberry Pi and peripherals, is strategically placed for easy access and maintenance. This design reduces exposure to harsh industrial conditions and minimizes maintenance costs. In Fig. 11, the ELP camera and the infrared light barrier sensor installed at the vibration feed continuously records images and sends them to the Raspberry Pi for processing, where algorithms process and analyze the images.

Figure 11. Sensor's setup

5.2. Processing and Material Throughput

Using the Raspberry Pi, the system processes images captured by the camera, identifying materials based on colour and other characteristics. During testing, the system could process approximately 300 to 1000 kilograms per hour. The materials do not need to be significantly spaced apart from each other, as the camera and sensors can handle continuous material flow. However, optimal separation is achieved with at least a minimal gap between objects to ensure accuracy.

5.3. Material Separation Mechanism

After classification, the system can be integrated with various material separation mechanisms, such as mechanical shifters, pneumatic systems, or conveyor belts with separate channels, depending on the industrial setup. However, in the current project, the actual separation has been done due to electrical conductivity.

5.4. Testing Results

As shown in Fig. 12 , the system achieved a 100 percent accuracy rate in detecting aluminium and copper, while for brass, it had a 93 percent accuracy rate with seven incorrect detections. Multiple metals on the conveyor belt were tested.

Metals	Recognition rates
Aluminum	100%
Copper	100%
Messing	93%

Figure 12. Recognition rate

Fig. 13 depicts the last scenario of our test, which is the detection of multiple metal pieces.

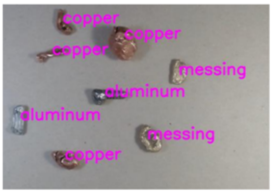

Figure 13. Multiple detection of metals

Fig. 14 shows those seven wrong-detected metals, which are all messing. The model predicts them wrongs as aluminium or copper; however, they are messing metals.

6. Machine learning in reducing costs

This section examines how machine learning reduces costs and simplifies industrial systems by optimizing processes and minimizing human intervention. Techniques like OpenCV, K-means, and decision trees have effectively lowered costs and complexity, improved productivity, and reduced errors, particularly in the mining and material recycling industries. In the following, these effects will be examined:

- Reducing energy consumption:
  Using machine learning algorithms, we have automated processes that previously needed constant human oversight. The system only activates when material is present, significantly reducing energy consumption by preventing devices from staying on standby unnecessarily.

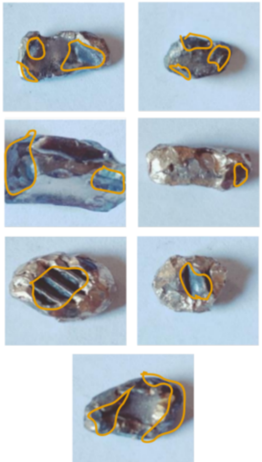

Figure 14. Wrong recognition of messing metal

- Reducing human errors and improving employee health:
  Automating material detection and separation reduces errors from human fatigue and improves working conditions by minimizing employee exposure to harsh, polluted environments and dangerous health risks.
- Increasing productivity and accuracy:
  Using decision trees and k-means for precise material detection brings about a host of benefits. It not only enables faster and more accurate data processing but also reduces the time required for material separation and recycling, thereby boosting the overall speed of the processes.

This research uses machine learning techniques like OpenCV, K-means, and decision trees to automate processes, reducing human intervention, energy consumption, and exposure to harsh environments. The system improves material detection speed, accuracy, and productivity while cutting operational costs and promoting sustainability. Using Raspberry Pi with motion sensors and LED notifications, it offers a cost-effective, efficient alternative to traditional methods. This approach enhances safety, accuracy, and scalability, leading to significant cost savings and more sustainable industrial practices.

Artificial intelligence systems can learn from collected data and improve over time however, some other researches have done with artificial intelligence also like [11].The article reports a 95.3 percent accuracy in detecting aluminium, showing strong model performance. Our algorithm, however, achieves 93 percent accuracy for brass and 100 percent for aluminium and copper. Unlike YOLO, which requires a high-performance GPU and focuses only on colour recognition, our approach allows for more flexibility and detailed material analysis, though further research is needed for size and shape identification. Deep learning models can increase processing time and require expensive hardware, raising costs. However, the time and financial savings are significant if similar or better accuracy can be achieved with simpler models.

In [17] the final evaluation part of the model does not refer to the accuracy of diagnosis and separation, but it mentions that the results obtained were favourable, and judging and comparing will not be easy. In [13] with ANN model achieved 74 percent accuracy in classifying aluminium, with 15 percent misclassified and 11 percent not classified at all. This highlights issues with accuracy that could impact industrial performance. The paper focuses only on aluminium, whereas our work examines three metals: aluminium, copper, and brass.

7. Conclusion and Future Works

This paper presents an intelligent, cost-effective system that uses image processing and machine learning to detect and separate metals on conveyor belts. Using Raspberry Pi and motion sensors significantly improves efficiency and accuracy while optimizing energy use in industrial processes. The system is versatile, with potential applications in various industries. Moreover, in the future, we will be able to recognize other material characteristics, such as the size, shape, or edges of the material, in addition to its colour. The more information we can get from the materials passing through the conveyor belt, the more we can help improve sorting and separating. Moreover, that includes having better cameras for machine vision scenarios and sensors that can detect even minimal materials by detecting their density.

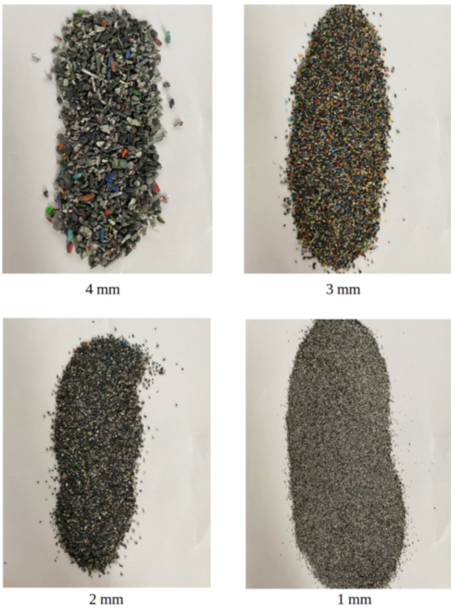

Figure 15. Different material with different sizes

Fig. 15 shows the different types of materials in 4 different sizes to be able to extract as much information from these materials will help the recycling process not only on the conveyor belt and regarding making the eddy current separator as bright as possible but also is helping to be able to have an eye on previous recycling machines where these materials come from. So by detecting and extracting as much information from existing materials, we can change the recycling standards and supervise the machines from a healthier and safer place, saving energy regarding human and energy resources.

It should be noted that the code of this research is available on GitHub [25] .

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