Software 2.0 for Scrap Metal Classification

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Abstract: Software 2.0 and its approach to the processing of multi-spectral images helping to perform an automatic classification of metal scrap is the subject of this research. The use of Machine Learning and Deep Learning tools contribute to the development of intelligent systems, allowing to achieve relevant results in the classification of images, particularly of metal scrap. In this research, tests will be performed with a multi-spectral chamber to obtain images of aluminum, iron, copper, brass, stainless steel, simulating an environment of metal scrap. The aim is to obtain the classification of these metals through the development of software and to perform a multi-spectral analysis of the obtained images. Preliminary tests were made in a controlled environment, with a small sample of these materials. Studies to implement a prototype in a Brazilian steel industry will follow.

1 INTRODUCTION

Steel is the world's most important engineering and construction material. It is used in every aspect of our lives. There are more than 3,500 different grades of steel with many different physical, chemical, and environmental properties. The European environmental initiative on raw materials (Parliament and Council, 2003) has recently promoted the efforts in recycling and recovery of metal alloys. Recycling of scrap plays an important role in the conservation of energy because the remelting of scrap requires much less energy than the production of iron or steel products from iron ore (Javaid and Essadiqi, 2003).

In Brazil, the collection of recyclable metal materials is carried out by a fleet of about 15 thousand trucks throughout the country. There are 1.5 million people directly and indirectly involved in the collection, selection, preparation and distribution of recyclable metal materials, including in this total 800,000 pickers (Vasques, 2009).

The objective of this work is the research of spectral images of scrap steel to perform an efficient classification using Machine Learning techniques. One of the goals is to facilitate a current visual and time-consuming human work, with many classifications that are dependent on personnel and fallible appreciation only.

Each year, U.S. industry discards tens of billions of pounds of non-ferrous metals as waste because it is either impractical or uneconomical to recover this material using current technology. Many alloys are downgraded in value due to contamination that cannot be cost effectively removed. In addition, billions of pounds of non-ferrous metals are shipped overseas to China and elsewhere, for separation into higher value scrap grades using low cost labor for visual identification and hand sort. Traditionally, metals businesses, including recycling, are slow in adopting new technologies. There are ongoing projects in US to transform this industry, by replacing old methods of manual selection and visual identification by fully automated, high-efficiency methods using computers, robotics, and other automation systems for material handling. This will have positive effects throughout the entire scrap industry chain. Scrap recyclers will be able to monetize the scrap value with a better and faster rating. The industries that use it, will be able to profit from the greater availability and quality of scrap, which will bring more competitive prices in the market. It is these reasons that lead government agencies in the United States, such as the National Institute of Standards and Technology (NIST) and the National Science Foundation (NSF) to develop new technologies aimed at advancing scrap processing tech-

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nology. Projects in this scope developed Spectramet[1], a platform of technologies for rapid identification that allows the unambiguous separation of non-ferrous mixed scrap according to the type of alloy (Spencer, 2005).

Steel is 100% recyclable, making it one of the most sustainable materials in the world. Even a sheet totally taken by the rust can be sent to processing in a steel mill gaining new possibilities of use (Zaparolli, 2014). Thus, recycling scrap iron and steel has remarkable economic and environmental advantages. The example of the steel industry is not unique, similar figures can be obtained with other materials, whether metallic or not. However, given its importance in the Brazilian economy, the values related to the steel industry really impress.

Recycling of scrap in new iron and steel products is advantageous, because in order to obtain a metallic product from iron ore (iron oxide) it is necessary to react it at high temperatures with coal, which in general removes the oxygen and isolates iron. This process has a very high energy expenditure, since it is necessary that certain regions of the furnace reach more than 2,000 degrees Celsius, the process generates many gases, particulates, solid wastes (called slag) and pig iron in liquid form. In order to produce steel from scrap, in general terms it is only necessary to melt the scrap (close to the same 2,000 degrees Celsius) and to correct the composition. These are relevant arguments in that recycling is much more advantageous, in relation to the production of the same material from iron ore, considering the consumption of raw material, generation of solid waste and gaseous effluents, necessity (usually for cooling, washing and heat treatment) and energy expenditure. Regarding this latest point, the energy expenditure, it is estimated that to make a kilogram of metal from the scrap, only 2/3 of all the energy that is consumed in the manufacture of a kilogram of steel from the ore is needed. Other interesting points are that recycling of scrap produces only 3% of the particulate matter and 30% of the solid waste that is produced with the production of steel from the ore, not counting very interesting gains in the gaseous emissions of nitrogenous and sulfur compounds, as well as simpler liquid effluents to be treated (Mancini, 2013).

Scrap iron arrives at steel mills in a large trucks, with cargo well accommodated, which makes it difficult to classify the cargo visually. Usually the heavy scrap is placed down and the small and mixed scrap

is placed over, for reasons of load optimization. This makes it difficult to verify the type of scrap shipped and the type of material that is below the visible load. In addition, purely personal and financial factors can influence the people who make the classification, leading to financial losses in the acquisition of scrap. It is intended that this task of classification be optimized in time and credibility, so that financial gains are obtained and improve the quality of the classification and separation of metallic scrap. Machine Learning[2] (ML) techniques will be studied, using images to obtain classification parameters that will help to classify metals. The application in the steel industry was taken into account both in the classification of the discharge of metal scrap acquisitions and in the preparation of scrap production, for use in the production of iron ingots.

The use of ML techniques for multi-spectral images is being used, due to the high cost of hyperspectral equipment. Although hyper-spectral equipment has valuable information in the images they produce, in most cases of study and implementation it is difficult to create proofs of concept, taking into consideration the price of the equipment. Also in the case of iron scrap materials, the issue of industrial secrecy creates legal obstacles to accessing images and information on similar projects, which are developed in other universities and research centers.

In a steel environment, there is a great need for correct sorting of scrap. The incorrect classification impairs the quality of the steel production, since it is cheaper to produce steel from scrap, the scrap should also be of good quality and with the quantities of suitable ferrous steel. In a steel production the incorrect selection of materials to go to the production of the pig iron can bring danger of explosion.

2 RELATED WORK

The author (Andrej Karpathy, 2018), a research scientist at OpenAI[3], was the first that use the term Software 2.0 on November 2017.

(Sikka, 2018) describes Sotware 2.0 as using the concepts of programming, mathematics, and statistics to develop the concept of ML, and put the machine into large-data reasoning. The results are presented

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[1]The initial system is located at Spectramet's technical research center in Greenfield, Mass., and will be dedicated to processing mixed non-ferrous metals from various sources.

[2]Machine Learning is a field of computer science that uses statistical techniques to give computer systems the ability to "learn" with data, without being explicitly programmed.

[3]OpenAI is a non-profit AI research company, discovering and enacting the path to safe artificial general intelligence.

as predictive behaviours of a given set of data, and can combine multiple characteristics, making it superior to human reasoning. This is the concept of ML as the basis of Software 2.0 and differs from the current standard in an important way: it is cantered on weights of neural networks[4], not explicit algorithms.

According to (Andrej Karpathy, 2018), neural networks are not just another classifier, they represent the beginning of a fundamental shift in how we write software. They are Software 2.0. The same author states that Software 2.0 platforms, must have a great development in the coming years, since their goal is not to replace but improve processes that the human being develops, or processes of analysis where the human being can't perceive the result, in cause of their complexity.

The author (Andrej Karpathy, 2018) says that, perhaps it is this human inability to understand some of the results made available by this Software 2.0 technology, which is its main disadvantage, according to the author, because in the event of system failure, it is presented as a "silent failure" that may also not be noticeable to the human being and to provoke a catastrophe without culprits.

According to (Domingos, 2015), we live in the age of algorithms. Few years ago, mentioning the word algorithm would have drawn a blank from most people. The same thing would happen to AI[5], who scarcely a few years ago frightened the citizen and the businessmen, with the presumption that AI would put the machines in command of the Earth.

According to the same author, it is necessary for people to be aware of ML, so that this learning of the computers will serve them, for me to decide and not others to decide for me.

The authors (Wilson et al., 2019), say that the recycling industry has been slow to adopt automated methods of sorting such metallic scraps. However, with the advent of hyper-spectral cameras and robotic-based picking and sorting methods, such procedures can now be performed automatically, relieving workers of laborious tasks while at the same time improving the efficiency of sorting metallic alloys. Since the automation process is more effective, scrap providers can produce more recycled material thus increase their profitability. According to the same authors, using automated systems, 40-50% of the steel that comes from recycled material and 30% of other metals can be sorted by magnetic drums or induction

or Eddy current separators[6], respectively. One of the greatest challenges in developing more sophisticated systems is sorting various non-ferrous metals such as aluminum, copper, silver, brass, lead, stainless steel, silver and gold.

A project that implement this concepts, was described by (Barnabé et al., 2015). The project uses spectral imaging to scrap classification and was referenced to the conception of a prototype combining two hyper spectral cameras, one ranging from visible to near-infra-red and the other covering short-wave infra-red, is presented. The prototype aims at the characterization of millimetre sized metallic alloys particles, originating from end-of-life vehicles and waste electrical and electronic equipment recycling.

Another work was published in a paper by (Kutila et al., 2005) and presents a novel automatic scrap metal sorting system which employs a colour vision based optical sensing system and an inductive sensor array sensor array.

Recently in 2017, the work in PICK-IT project, about Hyper spectral imaging in the VNIR[7], developed by a team, and described by (Braibant et al., 2017), has nevertheless proven to be an efficient technique to identify aluminum, zinc, copper, brass alloys and stainless steel. The same authors, describes an Hyper-spectral imaging in the VNIR has nevertheless proven to be an efficient technique to identify aluminum, zinc, copper, brass alloys and stainless steel (e.g., Barnabé et al., 2015, Kutila et al., 2005). The efficiency of hyper-spectral classification however depends on the surface conditions of the alloy fragments.

At USA, (Paul, Torek; Benjamin, Aubuchon; Kalyani, 2016) patented in 2016 a system and a method of sorting scrap particles, which includes imaging a moving conveyor containing scrap particles using a vision system to create an image. A computer analyzes the image as a matrix of cells, identifies cells in the matrix containing a particle, and calculates a color input for the particle from a color model by determining color components for each cell associated with the particle.

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[4]Artificial neural networks (ANN) are computing systems inspired by the biological neural networks that constitute human brains.

[5]AI, in computer science is artificial intelligence.

[6]Eddy current separator, it's a parasitic chain separator uses a powerful magnetic field to separate non-ferrous metals from the waste after all ferrous metals have been removed earlier by some magnet arrangement.

[7]The visible and near-infrared (VNIR) portion of the electromagnetic spectrum has wavelengths between approximately 400 and 1400 nanometers (nm).

3 BACKGROUND, MATERIALS AND METHODS

In the experiments already carried out, the materials used were aluminum, brass, copper, iron, stainless steel and painted iron materials to obtain multispectral images. For the analysis of these multispectral images, ML techniques were used, implemented with Python programming in the Anaconda platform. The images were obtained during the study design in different light conditions and distance for the photographed materials. The batches of images were cataloged according to the conditions of their obtaining.

3.1 Background

This study is based on multi-spectral image analysis techniques, applying a ML process that allows the obtention of marks that help making the classification of metals. Some of the techniques tested are the analysis of the RGB[8] band length, the color and the histogram of the image. The transformation of the image into matrix form, allows the use of multiple enhancement techniques, for improving image quality, such as:

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- Contrast stretch;
- Density slicing;
- Edge enhancement;
- Spatial filtering;
- Noise reduction;
- Improve contrast image;
- Extract RGB information;
- Removing background;
- Image histogram information.
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A multi-spectral image of the used materials is a set of several monochrome images of the same material, each obtained with a different sensor. Each image is referred to as a band RGB. A multi-spectral image is an RGB color image that is composed of a R-red, G-green, and B-blue image each obtained with a sensor sensitive to a different wavelength.

All single-band imaging operations can also be applied to multi-spectral images by processing each band separately. Using the matrix of a multi-spectral image, we can detect the edges on each band to extract an image from each band. If we want to go back to the original image, we simply assemble three images using mathematical calculation of the matrices that make up each image.

The transformation of the RGB bands of an image into matrices and lists allows an approach with

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[8]RGB is the acronym of the additive color system formed by the initials of the colors Red, Green and Blue.

ML, and the differences between the spectral bands of the different materials can be exploited mathematically. Several libraries available for image processing allow an exploration at the level of the representative matrices of an image, its color and the reflectance as exposed to the incidence of light. Some of the applied techniques are of marking objects in the images and extraction so that the analysis is not influenced by noise.

To explore the additional information that is contained in the various bands, we must consider the images as a multi-spectral image and not as a set of monochromatic gray scale images. The overall goal of image sorting is to categorize automatically all pixels of an image in classes. The multi-spectral data are used to perform the classification and spectral pattern within the data for each pixel is used as the numerical basis for categorization. The different types of resources manifest different combinations of numbers based on in their inherent spectral reflectance and emission properties.

3.2 Materials

The used equipment is a multi-spectral machine, ADC Lite (COMPUTAR, 2009), which is a lightweight (198 grams) version of ADC Air Camera. The camera and its accompanying software, PixelWrench2, is used to capture and process multi-spectral images. The Figure 1 has the equipment used.

Figure 1: Equipment used in the tests.

The equipment can be used manually or coupled to a drone to obtain the images in an outdoor environment, as with industrial scrap. The method used consists of capturing images in a controlled lighting environment and to clean the artefacts used in the images. The chosen materials were iron, copper, brass, aluminum, stainless steel and copper wire. These materials represent metallic materials, which must be separated from the scrap yard in a steel industry. The workbench is presented bellow, at Figure 2.

The Anaconda framework was installed to use

Figure 2: Working environment and samples of metallic material.

Jupyter with Python programming. The exploration of the bands of the images focuses on the analysis of the matrices of the images, in order to obtain classification parameters for the different materials. Another approach could be to use Google's Collaboratory, which provides a Python virtual machine in the cloud and can also use the GPU's[9] environment.

Applied techniques used need Python libraries installed, such as: Pillow, Opencv, Openpyxl, Colormath, Webcolors, Numpy and Matplotlib, provide a set of facilities that allow us to analyse different issues and compose a specific approach to each problem.

3.3 Methods

For the study, several photos of all materials were generated and stored in separate folders, identified by each type of conditions of image acquisition. In each batch of images, the following conditions were changed: the lighting conditions, background image of the place where the images were taken and the distance between the camera and the materials. The images are generated in TIF[10] format and converted to other formats using the PixelWrench2 software, provided with the Tetracam machine.

All the images were classified according to the type of material, so as to be able to have a database of multi-spectral images, that can be used in future ML processing.

A Python program was developed to read all images from a folder and submit each image to various techniques, to retrieve image characterization information. Following are examples of information obtained:

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- Extract each channel image;
- Maximum and minimum histogram values;
- Histogram plotting;
- Spatial filtering;
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- Contrast stretch;
- Edge enhancement;
- Removing Background;
- Extract RGB information;
- Obtain delta from colors;
- Most common colors;;
- Image histogram information;
- Extremes from each band spectrum.
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This information is stored in a Pandas DataFrame table, for each analysed image. Some information from the table, are printed in Figures 3 and 4.
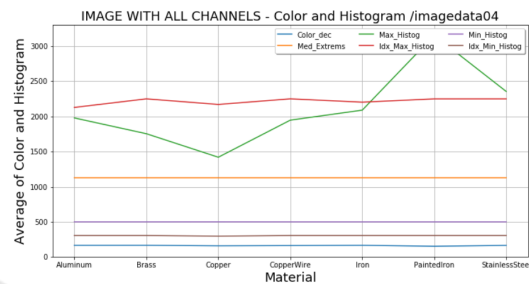

Figure 3: Plot the information about materials.

Classifications can be obtained by combining several parameters and are stored in a database. This database will be the basis of the training system for future classifications.
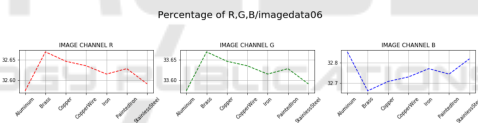

Figure 4: Analysis from image material bands.

After its processing, the information in the Pandas[11] table is stored in a database, and will serve as a basis for ML processing the information about the analysed materials. Figure 5 presents the database.

4 ANALYSIS AND DISCUSSION

The techniques studied address several problems of a steel environment: materials that are in dispersed positions and in external environments, influence of the luminosity, image noise caused by the external environment, or by the factory floor, painted or dirty material and material with a lot of reflectance normally shown for example in stainless steel.

For suppressing images and background colors, and also suppressing colors in the environment where

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[9]GPU, Graphics Processing Unit.

[10]Tagged Image File Format (TIFF) is a standard file format used in the publishing and printing industry.

[11]Pandas is a software library written for the Python programming language

Folder	File	Material	Size	Forma	Mode	All_Bands	Sum_Ch0	Sum_Ch1	Sum_Ch2	Histogramer_ele	Color	Color_RGB	Color_hex	Color_dec	Med_Extreme	Max_Histog	Max_Hist	Min_His
imagedata01	aluminum_001.tif	aluminum	(2048, 153	TIFF	RGB	545,0683	183,2617	183,2617	178,5449	94,37184	768	white	(255, 255,	#ffffff	16777215	105,333333	61168	46
imagedata01	aluminum_002.tif	aluminum	(2048, 153	TIFF	RGB	540,9366	181,8844	181,8844	177,1678	94,37184	768	white	(255, 255,	#ffffff	16777215	117,166667	60230	50
imagedata01	aluminum_003.tif	aluminum	(2048, 153	TIFF	RGB	618,9766	207,8982	207,8982	203,1802	94,37184	768	white	(255, 255,	#ffffff	16777215	92,1666667	74860	51
imagedata01	aluminum_004.tif	aluminum	(2048, 153	TIFF	RGB	870,5704	291,7719	291,7719	287,0266	94,37184	768	white	(255, 255,	#ffffff	16777215	133,5	39307	32
imagedata01	alum_001.tif	alum	(2048, 153	TIFF	RGB	545,0683	183,2617	183,2617	178,5449	94,37184	768	white	(255, 255,	#ffffff	16777215	105,333333	61168	46
imagedata01	alum_002.tif	alum	(2048, 153	TIFF	RGB	540,9366	181,8844	181,8844	177,1678	94,37184	768	white	(255, 255,	#ffffff	16777215	117,166667	60230	50
imagedata01	alum_003.tif	alum	(2048, 153	TIFF	RGB	618,9766	207,8982	207,8982	203,1802	94,37184	768	white	(255, 255,	#ffffff	16777215	92,1666667	74860	51
imagedata01	alum_004.tif	alum	(2048, 153	TIFF	RGB	870,5704	291,7719	291,7719	287,0266	94,37184	768	white	(255, 255,	#ffffff	16777215	133,5	39307	32
imagedata01	brass_001.tif	brass	(2048, 153	TIFF	RGB	851,9313	285,5531	285,5531	280,8251	94,37184	768	white	(255, 255,	#ffffff	16777215	135	41589	60
imagedata01	brass_002.tif	brass	(2048, 153	TIFF	RGB	787,7716	264,185	264,185	259,4015	94,37184	768	white	(255, 255,	#ffffff	16777215	136	45750	58
imagedata01	brass_003.tif	brass	(2048, 153	TIFF	RGB	837,4827	280,7422	280,7422	275,9983	94,37184	768	white	(255, 255,	#ffffff	16777215	133,5	32863	38
imagedata01	copper_001.tif	copper	(2048, 153	TIFF	RGB	638,9709	214,563	214,563	209,8449	94,37184	768	white	(255, 255,	#ffffff	16777215	133	63026	34
imagedata01	copper_002.tif	copper	(2048, 153	TIFF	RGB	708,8747	237,8642	237,8642	233,1463	94,37184	768	white	(255, 255,	#ffffff	16777215	133,5	51131	41
imagedata01	copper_003.tif	copper	(2048, 153	TIFF	RGB	872,2666	292,41	292,41	287,4466	94,37184	768	white	(255, 255,	#ffffff	16777215	133,5	167890	252
imagedata01	copper_004.tif	copper	(2048, 153	TIFF	RGB	752,4307	252,384	252,384	247,6626	94,37184	768	white	(255, 255,	#ffffff	16777215	133	45917	32
imagedata01	copper_005.tif	copper	(2048, 153	TIFF	RGB	677,703	227,4739	227,4739	222,7553	94,37184	768	white	(255, 255,	#ffffff	16777215	133	46121	31
imagedata01	iron_001.tif	iron	(2048, 153	TIFF	RGB	677,703	227,4739	227,4739	222,7553	94,37184	768	white	(255, 255,	#ffffff	16777215	133	46121	31
imagedata01	iron_002.tif	iron	(2048, 153	TIFF	RGB	578,6535	194,4576	194,4576	189,7383	94,37184	768	white	(255, 255,	#ffffff	16777215	132,833333	59164	57
imagedata01	iron_003.tif	iron	(2048, 153	TIFF	RGB	792,5258	265,7822	265,7822	260,9615	94,37184	768	white	(255, 255,	#ffffff	16777215	134	70494	252
imagedata01	painted_iron_001.tif	painted	(2048, 153	TIFF	RGB	669,7991	224,8393	224,8393	220,1205	94,37184	768	white	(255, 255,	#ffffff	16777215	105	59983	77
imagedata01	painted_iron_002.tif	painted	(2048, 153	TIFF	RGB	774,6524	259,7893	259,7893	255,0739	94,37184	768	white	(255, 255,	#ffffff	16777215	111	60017	78
imagedata01	painted_iron_003.tif	painted	(2048, 153	TIFF	RGB	888,7216	297,8134	297,8134	293,0948	94,37184	768	white	(255, 255,	#ffffff	16777215	134,5	65328	69
imagedata01	plasticised_copper_w	plasticised	(2048, 153	TIFF	RGB	831,1114	278,6287	278,6287	273,854	94,37184	768	white	(255, 255,	#ffffff	16777215	134	52906	22
imagedata01	plasticised_copper_w	plasticised	(2048, 153	TIFF	RGB	814,57	273,1071	273,1071	268,3558	94,37184	768	white	(255, 255,	#ffffff	16777215	134	49536	22

Figure 5: Database obtained by automatic processing of images with Python.

Figure 6: Image noise removal technique using brass.

the images are obtained, there are some issues resultant from changes on each environment. As an example, the influence of the floor colors of the scrap yard must be configured in the system to be disregarded from the analysis. Some of this techniques are presented in Figures 6 and 7.
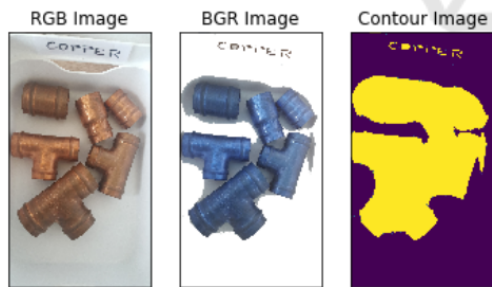

Figure 7: Techniques for area detection for copper metal analysis.

The use of mathematical computations in multispectral array of images is a process that demands a lot of computer power in terms of processing and memory. One approach was to use Google's Colaboratory, with the project using the cloud and the GPU provided in that environment. The transfer of images between the source environment and the cloud should be scoped, because the large amount of information in the images generates a large volume of data traffic to the cloud. Another approach is to install the software on a computer with a fair amount of memory and processing power and with a performant GPU. This was the approach used in the study. This facilitated the handling of images in large quantities and with the required speed, in terms of what is expected in the implementation of the prototype.

The similarity of color between various materials and the perception of color noise to the surrounding area, needs algorithms that make a tolerance in the color detected. The algorithm implements a color difference to understand which it is the color sought. Colormath libraries provide features that allow us to work in this area using Python. In this case the conversion between color formats, decimal and other forms of expression require functions developed using mathematical expressions with Numpy Python libraries. Normally we do not look for a fixed form of the spectrum, but an approximate color. That depends on the conditions of luminosity in which the images were obtained and the level of dirt of the materials.

In a first step, the image was submitted to techniques that improves contrast. Contrast stretching or normalization, is one such operation applied on images, which improves the contrast of the image so that the details present in the image can be clearly seen. See Figure 8, produced with this technique.

Figure 8: Contrast enhancement technique for better image analysis.

After that step, we extract the analysis area in an image, detecting its contours, extracting the relevant

part, thus removing the influence of its background. This technique makes up Edge Enhancement, that delineates the edges surrounding various objects of interest and makes the shapes and details comprising the image more conspicuous and perhaps easier to analyse. Figure 9 presents this technique.

Figure 9: Plotting extract area to brass histogram.

The background of the image was removed using techniques of delineation of the contour of the materials, and an auto background with expressive color was generated. In this case, the color red was used. Techniques were applied to the image obtained from the contour, disregarding the colors that remained in the middle of the materials. This eliminates noise in the image and obtains more assertiveness in the analysis.
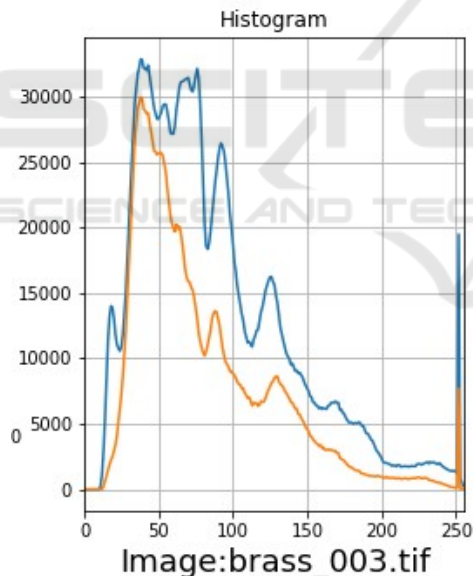

Figure 10: Plotting brass histogram.

The Opencv libraries for Python have functionalities directed to these imaging techniques. The features have been developed so that they can be adjusted to the background and context colors where image techniques can be applied. For example, in a black floor scenario, the colors at the threshold of black should be considered as image noise. Figure 10, presents this technique, using Opencv.

Using the histogram image information we can obtain more technical and visual information. His-

tograms plots how often each intensity value in the image occurs. Histograms help detect image acquisition problems, like:

- Over and under exposure;
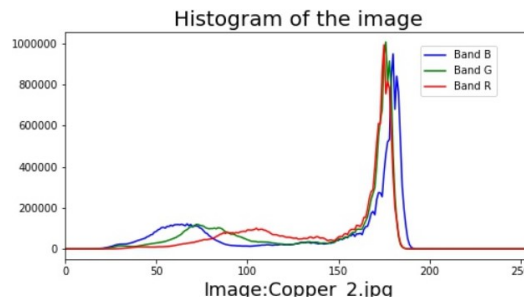- Brightness;
- Contrast;
- Dynamic range.

Figure 11: Copper histogram analysis.

Some point operations can be used to alter histogram, e.g: Addition, Multiplication, Exp and Log and Intensity Windowing (Contrast Modification).

Another issue to consider is the color list used in the algorithms. Depending on the library used and the algorithms to implement, each library has its list of colors. Colour analysis can be made using Matplotlib, or Webcolors colors as a list of valid colors, to give two examples of used libraries that already have color lists. For development purposes, a fixed color list defined was implemented. This color list has the purpose of serving the color search algorithms in the context of what is sought.

5 ONGOING WORK

The parameters with higher information were obtained from the histogram of the image. Each material has its signature in terms of the spectral image, both the intensity of its brightness and the positions of the spectrum, where that maximum is presented. The minimum values' positions of the spectrum also show variations in some materials. This information is obtained by removing each band of the image. After we analysing the maximum value of the spectrum matrix and its position, in the list of values obtained (position in the spectrum). The visualization of this information for copper and brass, can be observed in Figures 10 and 11, where the difference in the parameters is verified in particular in: MaxHistog, IdxMaxHistog and IdxMinHistog. At the level of the spectral analysis of each of the bands we have differences between the band R (Red) and B (Blue) that could be

observed after a more accurate analysis of the values of the spectrum, obtained by multiplying its values by a thousand. The projection of these values presents a relevant difference, which would not be observed in Figure 4.

6 CONCLUSIONS

We have already some ML techniques that may allow to sectorially develop processes of classification of metals. Not all metals have the same approach and some require several parallel approaches to achieve classification. Depending on some types of metal scrap grading requirements, some techniques will only be possible using Deep Learning. In this case, the classification of metals is inserted in the acquisition process, where the technique must be different given the large volume of metal that is to be inspected, and given that it is loaded by truck.

With this approach of ML applied to the images, it is intended to obtain its classification in terms of the type of metal used in its composition. Additional ML methods allowing an analysis of the materials color are used, so that a phased classification of the materials can be done. One of the factors to be considered is the conditions of luminosity in obtaining the images, and the cleaning of the materials involved in the images. In an industrial scrap environment, it will not always be easy to obtain optimum results for the imaging process, so industrial prototype application studies should address this issue.

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