ELE 402 - GRADUATION PROJECT II
FINAL REPORT

HACETTEPE UNIVERSITY
DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

PROJECT TITLE: Material Classification using Thermal Imaging

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ABSTRACT

In recent years, waste management and need for recycling has gained importance more than ever due to the increase in population. Because of this reason, making recycling easily applicable and available with reasonable cost is very crucial. Mainstream recycling methods rely on human effort hence there is a room for automatization. The most potentially improvable step of the recycling is the classification of materials in which solid wastes are classified with respect to their materials. In this work, an alternative method to classification step in mainstream recycling is proposed. Proposed method includes an active heating unit that consists of 3 thermal lamps. It also includes a FLIR T420 thermal camera. Objects to be classified with respect to their material are heated using the heating unit, then left for passive cooling. The process is observed using the thermal camera. Obtained images are then used in machine learning methods for classification. The proposed method aims to automatize the classification step in recycling as well as making it cheaper and easily applicable. The accuracy of the system is calculated in the dataset that is collected in our lab.

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1.INTRODUCTION

With the increasing population and uncontrolled urbanization, the damage being applied to nature by human beings are increasing day by day. One of the major factor of this destructive effect on nature is caused by the waste problems. One of the research shows that the expected global waste will be reached 2.2 billion tonnes by 2025 [1]. To overcome this problem our most important tool is recycling. But the offered solutions to this problem are not adequately automatized and accessible even today standards.

Solid wastes need to be separated during the recycling process. Because each waste has a different chemical characterization and needs to be classified accordingly. To overcome this problem, there have been many solutions offered, one of the most common way that's been used today is to separate solid wastes according to their sizes by using some sort of sifting method as called; "Size separation of particulates in a trommel screen system, 2010". As it can be understood by it's naming there is used a big trommel that has various sized holes on it. This trommel is been turned and by that way, bigger materials are separated.

Another way that has been used is airflow system. In this system, there is airflow applied to solid wastes. In that way wastes have less densities (like paper or cardboard) flows and separated from higher density materials (like iron or concrete).

Magnetic separation is another way being used to separate wastes. As the naming suggests, there is a strong magnet is used to separate ferromagnetic materials (iron, copper, chromium etc.) are separated from diamagnetic materials (paper,cardboard, etc.). This method is used especially for separating valuable metals.

In addition to methods that have been told above, there is a method used called : " Using thermal camera detection to separate solid wastes". Today there is little or no research about this method. In the research a heating source applied to solid waste and heating - cooling reactions were observed with the help of a thermal camera. After the observations, heating characteristics of the material is logged and classified to separate from other types of materials.

In our research, we will introduce a new alternative method to the classification of municipal waste materials. Thermal visualization technology may be a cheaper and more accurate alternative to methods that being used today. Besides these advantages, this method requires holding materials at a constant temperature.

In the remaining pages we will explain this method in a more detailed manner with different headlines.

2.PROJECT DESCRIPTION

Waste is any substance which is discarded after primary use, or is worthless, defective and of no use. Recycling is a chain of processes that aim to reuse waste materials that would otherwise be thrown away as trash. It can benefit our community and the environment. Recycling protects the natural resources on earth, reduces the need for new raw materials and saves energy. This process is very important and should be considered, as it has both environmental and economic impacts.

This project aims to classify and define objects with the help of thermal imaging and machine learning algorithms. Every object has distinct heating and cooling curves. This Thermal characteristics of the objects can be easily observed and classified with the help of thermal imaging techniques. In our project, we benefited from a phenomenon as called: "Emissivity".

Emissivity [2] can be described objects surface effectiveness of emitting energy as a thermal radiation. In many cases, this thermal radiation can't be observed with a human eye. Thermal cameras can detect the infrared radiation which every objects constantly radiates every time. (All real objects have emissivities less than 1.0, and emit radiation at correspondingly lower rates.)

Materials	Emissivity
Aluminum foil	0.03
Brick	0.90
Glass	0.96
İron	0.06
Paper	0.86-0.88
Teflon	0.85
Water	0.96

Table 1

Here you can see some materials and their emissivity values.

The rate of heat transfer by emitted radiation is determined by the Stefan-Boltzmann law of radiation:

$$\frac{Q}{t} = \sigma e A T^4$$

This formulation shows us that emissivity is inversely proportional to the time to heat. So the higher the object has emissivity, heats in a shorter time.

In this project we will not directly use emissivity phenomena but it's useful to know background knowledge about heating and cooling times of objects.

After the given information about how the objects have different heating characteristics now, we can talk about the way we used to detect and define the objects.

Experiment setup: In this project, our setup consists of; 3 Heating lamps, a Thermal camera, a handmade ramp for putting heating lamps, different waste objects to observe heating characteristics and a computer to classify and train collected data.

We used Osram brand 100w R80 lamps as a heating source in our model. Lamps put a certain measured distance and angle along our data collecting process. This is important to collect true data which latter be used to compare with other data.

In our project, we used a FLIR T-420 thermal camera to observe infrared radiations of objects during heating and cooling process. This camera has 320x240 pixel rate and 30 FPS maximum framing. Even the thermal camera brings the image with a single channel, images are colored using color mapping to obtain sharper more detailed images. Thermal camera provided us by our Engineering department.

Fig 1 First prototype setup for collecting data from different materials

After the observation has been made, video of heating and cooling processes are recorded. The recorded data is is transferred into a computer in order to apply image processing and machine learning techniques.

The experimental procedure consists of three parts: data acquisition, data processing and training, testing and evaluating machine learning classifiers.

We record the change in video using our experimental setup for each object in the data acquisition section. Heat lamps are turned on for a specific amount of time (i.e. 5, 10, 15 ... seconds) to stimulate the object. Afterward, an object is left for cooling for a specific amount of time (i.e. 5, 10, 15 seconds) without any active cooling. The whole cycle (heating phase and the cool down phase) is recorded using the thermal camera.

In the data processing section, Using image processing techniques, the gathered video footage will be examined, and the images will be processed appropriately. It will go through some algorithms for this. We will examine the thermal characteristic information from these data.

3.ENGINEERING STANDARDS AND DESIGN CONSTRAINTS

3.1.ENGINEERING STANDARDS

This project will use the IEEE Standard for Artificial Intelligence (AI) Model Representation, Compression, Distribution, and Management [5].

This standard defines AI development interface, AI model interoperable representation, coding format, and model encapsulated format for efficient AI model inference, storage, distribution, and management. This standard provides efficient toolsets for inference, compression, decompression, coding, and packaging of the AI model that breaks down the AI model's barriers between different computing architecture and algorithm frameworks, storage cost, as well as protects business sensitive information.

Our project is to classify waste object using thermal characteristic, some machine learning and AI algorithms. This standard is necessary because tools and algorithms for artificial intelligence and machine learning will be widely used in this project.

3.2.DESIGN CONSTRAINTS

- **Electromagnetic Radiation Issues**

  In this project, A thermal camera is used to collect data. Thermal imaging is a method of using infrared radiation and thermal energy to gather information about objects, in order to formulate images of them, even in low visibility environments. Thermal imaging is based heat which is emitted from all objects. This energy from an object is also referred to as the "heat signature", and the quantity of radiation emitted tends to be proportional to the overall heat of the object. The amount of radiation used by the thermal camera in imaging is harmless.

Budged Limitations

The thermal camera (FLIR T-400) to be used in this project calibrates itself after a certain period of time. This problem is caused by the thermal camera. Unfortunately, due to budget problems, we will try to solve this problem in software.

- **Designs that help solve common international and national problems**

Waste is increasing day by day due to the rapid increase in the population of the worldThis situation contributes to increased environmental pollution and the depletion of earth's resources. That's why recycling is so important. Correct classification of waste is a time-consuming task in recycling. Our project is to classify waste object using thermal characteristic and some machine learning algorithms. This system is contactless and non-destructive, therefore it is suitable for a wide range of application scenarios.

- **Honesty, truthfulness, and openness in the design and the report**

In this project, we will share the design we made, the codes we will write and the report in an accurate and open source manner.

- **Designs that can be physically implemented**

We have physically realized the design that we will use to collect data in this project and we will continue to use this setup.

- **Designs that support future upgrades**
- The design that we will use to collect data in this project can be improved in the future and we want to realize this. Additionally, the software design to be used in the project will be designed in such a way that it can be developed in the future and the addition of new algorithms.

4.SUSTAINABLE DEVELOPMENT GOALS

As we mentioned in the introduction section, our main goal is to take action against the increasing human waste and the devastating effect of climate change on our planet. To avoid that our main focus is recycling. By doing the recycling process we can effectively regain the sources we wasted and reduce pollution at the same time. Because recycling prevents pollution caused by harvesting new raw materials. Additionally, recycling helps the saving energy. For example[6], recycling aluminum can saves %95 of the energy required to harvest from its raw material source. One ton of recycled aluminum saves 14000-kilowatt hours of energy (Kwh),40 barrels of oil, 130 152.32 million BTU’s of energy and 10 cubic yards of landfill space.

Recycling also creates new job opportunities and causes positive feedback from society. The study [7] found that in a single year, recycling and reuse activities in the United States accounted for:

681,000 jobs $37.8 billion in wages; and $5.5 billion in tax revenues.

To apply all the procedures we mentioned above, we need to implement recycling by using cost-effective and applicable methods. Recycling proceeds with 3 steps.

Step 1 ; Collecting and processing, Step 2; Manufacturing, Step 3 ; purchasing new products from recycled materials.

Our main concern in this project is step 1 which is the most important part. Because this part directly affects cost-effectiveness and productivity of the recycling process.

In this project, we introduce a method that is fairly new one hasn't yet been implemented in recycling facilities. To increase the productivity of recycling wastes, we need to separate materials from each other accurately. Because each material has different chemical characteristics hence different recycling processes. Our method, as we've explained in detail in earlier sections, may be much more efficient than promised methods that had been used until today.

Thermal cameras are widely used in many areas and are being developed every year. Also, thermal cameras are much more precise to detect different materials by using their heat characteristics. And most importantly it is easy to apply or modify current recycling facilities. With referring to the stated reasons above, our project can make a huge impact on recycling and reducing climate change indirectly.

5.BACKGROUND

5.1BACKGROUND ACQUIRED IN EARLIER COURSE WORK

In this project, our effort mainly focus on collecting data and knowing how to process it by using related software programs. To do that there are several courses that have critical importance to complete the project successfully.

First of all, data that will be collected are just frames that have different color pixels according to their heat condition. These frames need to be processed so they can be applicable to related software. To do that we can use our knowledge in ELE 120 programming course. This course helped us to understand the requirement of using the software. Also helped us to process the input in coding environment. Such input can be framed as we mentioned. We will benefit many libraries, algorithms, and data structures to fulfill such purpose.

While developing this project, we will develop software using machine learning. For this, it is also very important to know the Data Structures course. We know data structures (stack, queue, tree, graph) in this course. Knowing these data structures will help our software and algorithms and ensure that it is efficient by taking the ELE411 course.

Algorithms for machine learning are driven by calculus. It would be impossible to predict results using a given data set without understanding its concepts. Calculus helps to analyze the rate at which quantities change, and is concerned with the optimum performance of machine learning algorithms. Some of the necessary topics to ace the calculus part in machine learning and data science applications are "Differential and Integral Calculus, Partial Derivatives, Vector Values Functions, Directional Gradients". We learned these topics in ELE123 and ELE 124 Calculus courses.

We also learned Linear Algebra ELE235 and ELE236 Differential Equation courses. Linear Algebra is concerned with vectors and matrices, and mostly revolves around computation. It is essential to the machine learning and deep learning processes. Linear algebra is applied in machine learning algorithms in loss functions, regularisation, covariance matrices, Singular Value Decomposition (SVD), Matrix Operations, Support vector machine classification, and Linear regression.

Machine learning is the process of creating prediction models from ambiguous data. Statistics is the main part of mathematics for machine learning. Also, Probability Theory is required to predict the set of outcomes. Some of the fundamental Statistical and Probability Theory needed for ML are Combinatorics, Probability Rules & Axioms, Bayes' Theorem, Random Variables, Variance and Expectation, Conditional and Joint Distributions, Standard Distributions (Bernoulli, Binomial, Multinomial, Uniform, and Gaussian). We learned about these topics in ELE 302 Probability Theory.

Addition to all of this, there is also required to strong mathematical knowledge to process frame inputs into signals that will be meaningful for our program. We will use our knowledge from the ELE301 Signals and Systems course. As we mentioned before,

we will use a thermal camera in this project. Simply as the working principle of this thermal imager, the Signal and Systems course helped us a lot. Our thermal camera has a certain FPS value. This gives us information about how many frames we will get per second. In that course, we learned sampling theory. Sampling is required to create meaningful and processible data from input frames. Basically, recorded frames will be included the heat information for each pixel, this information dependent on time but, we need the samples periodically. So as the sampling theorem stated:

$$\mathrm{x}_s(t) = x_c(t)\delta(t) = x_c(t)\sum_{n=-\infty}^{\infty}\delta(t-nT)$$

$$\mathrm{x}_s(t) = \sum_{n=-\infty}^{\infty} x_c(nT)\delta(t-nT)$$

Means that our continues input signal sampled with some period T using impulses.

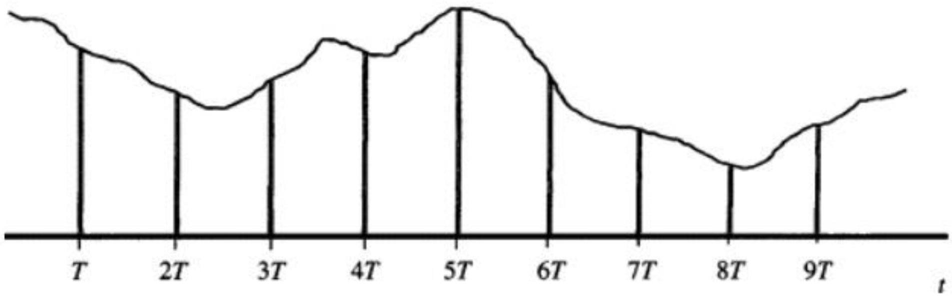

Figure 2: Sampling Continuous Signal [8]

5.2 BACKGROUND ACQUIRED THROUGH ADDITIONAL RESEARCH

- **Thermography**

Thermography is a technique that involves a heating element and an infrared camera to inspect the material properties of a target object. The heating element injects heat into the object, and then the IR camera gets the temperature data of the heated region. [9] Thermography as a field has been around since the 1980s. It has been used by the industry as a nondestructive testing and evaluation tool. [10]

- **Machine Learning**

Machine learning is a field of study that looks at using computational algorithms to turn empirical data into usable models. [11] Computer systems perform functions through machine learning such as clustering, calculations, and pattern identification. The learning process is attained using various algorithms and arithmetic structures to analyze the information. Machine Learning is used to find a relationship between the features and some output values called labels.[12]

Machine Learning process starts with inputting training data into the selected algorithm. These used data can be known or unknown data. The algorithm is trained with this data. Then the trained algorithm is tested with test data. If the prediction is not as expected, the algorithm is retrained multiple times with data until the desired output is found. This enables Machine Learning algorithm to continually learn on its own and produce the most optimal answer.

There are so many different types of Machine Learning systems. We will be interested human supervision systems.

- Supervised Learning

Supervised machine learning creates a model that makes predictions based on evidence in the presence of uncertainty.

- Unsupervised Learning

Unsupervised Learning uses machine learning algorithms to analyze and cluster unlabeled datasets.

In this project, we will focus more on supervised learning. Supervised machine learning is the construction of algorithms that can produce general patterns and hypotheses by using externally supplied instances to predict the fate of future instances. [13]

The first step is collecting the dataset for Supervised Learning. These data are processed and a data set is created. In this project, we will use the Python programming language and we will use various libraries for these datasets, such as pandas. Most of this data is used to train the machine learning model. The remaining data is used as test data and the trained model is tested with that data. The accuracy and efficiency of the model are then calculated.

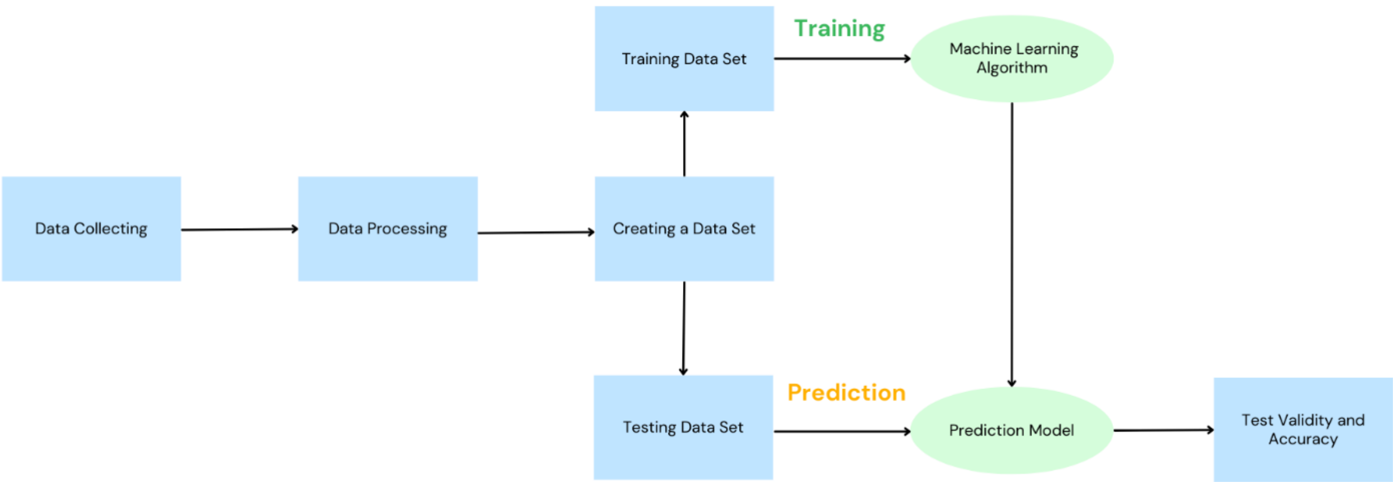

Figure 3. Supervised Learning Methodology

As mentioned before in the report , we will use Python in this project and Sci-kit Learn will be used in these training and prediction models.

The most effective and reliable Python machine learning library is called Sklearn (Scikit-Learn). It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction in Python.

Here are some of the most important supervised learning algorithms :

- k-Nearest Neighbors
- Linear Regression
- Logistic Regression
- Support Vector Machines (SVMs)
- Decision Trees
- Random Forests
- Neural networks

6.METHODS

There are various methods to realize this project and reach the result. This project will use thermal imaging and machine learning for material classification.

We determined some steps to realize this project and the methods were determined according to this step.

Figure 4 methodology

Data Collecting: There are multiple ways for this phase. In our project, we used a Thermal Camera to observe infrared radiations of objects during heating and cooling process. This camera can record with different techniques (Gray Scale, Colored Scale) and temperature limits can be set on the recordings. We can set our records accordingly.

Data Processing: Different Python libraries can be used for this stage. At this stage, mostly image processing techniques will be used. The progress of this stage may vary depending on the technique used.

Training & testing and evaluating algorithm: Different Python libraries can be used for this stage. At this stage, mostly artificial intelligence algorithms will be used. Multiple algorithms can be used for this, like SVM, CNN, KNN. The progress of this stage may vary depending on the technique used. There are many methods that we thought but we focused on two methods to realize this project. All these methods are considered based on the experimental setup prepared.

6.1 METHOD 1

In this method, we will use various algorithms, libraries to achieve our goal.

- **Data Collecting**

Thermal images of different materials are needed for classification. In this method, it will be considered to save these thermal records as "Gray Scale".

Grayscale is a range of gray shades from white to black. Grayscale is achieved by assigning a single value to each pixel in an image, with black being the lowest value and white being the highest. There are several advantages to using grayscale techniques in image processing. One of the main benefits is that this technique can reduce the amount of data required to store an image. Grayscale images also tend to be easier to process and analyze than full color images, since they only have one channel of information as opposed to three. This can make certain image processing tasks, such as edge detection or pattern recognition.

One potential disadvantage of grayscale techniques in image processing is that they can reduce the visual richness and detail of an image. This application will not have any disadvantages for this method.

In addition, the maximum and minimum temperature values of the camera will be fixed before the recording. Thus, as long as the object is heated, the maximum temperature will not change and the results will be more accurate in thermal recording.

- **Data Processing**

After the necessary data are obtained, these data must be processed appropriately to make them meaningful. There are various image processing libraries in Python for this. In this method, OpenCV will be considered.

First of all, the records we obtained belong to the materials that we will classify in this project. The thermal camera records at 30 FPS. In this section, we will examine each frame separately. This recorded image has some noise. We will try to reduce noise in images by passing each frame through an appropriate filter. Then we will focus on the part of this image that contains the material and we will take average of each frame to get a pixel density. There are various techniques to reduce noise in images.

- Median filter
- Gaussian filter
- Bilateral filter
- Wiener filter

We are considering using a Gaussian Filter in this method. This is a linear filter that uses a Gaussian function to weight the surrounding pixels of each pixel. It is commonly used to smooth images and reduce the effects of noise and sharp edges. This filter will reduce noise and make the result more accurate.

One potential disadvantage of this is that they can not preserve edges in image.

- **Training, testing and evaluating algorithms**

After the applied image processing techniques, artificial intelligence algorithms suitable for these data will be selected. These algorithms are simply divided into Supervised and Unsupervised.

Supervised Learning

Supervised machine learning creates a model that makes predictions based on evidence in the presence of uncertainty.

Unsupervised Learning

Unsupervised Learning uses machine learning algorithms to analyze and cluster unlabeled datasets.

It is thought that Supervised Learning will be used in this method. Labeling will be done for each data and the resulting time series will be labeled. Thus, the algorithm to be used will be trained with these tags.

- Support vector machines (SVMs)
- Decision trees
- Random forests
- Gradian Boosting
- KNN
- Neural networks

This method would be tested in the supervised algorithms above and the appropriate method would be used according to the accuracy of the result. After this training, some neural network algorithms can be added according to the required results. These algorithms are aimed to increase the accuracy of the result.

6.2 METHOD 2

In the second method, instead using the gray scaled thermal records as in previous method, we were planned to use "RGB" scaled images or frames in data collecting section.

RGB Image Processing:

RGB image basically means combination of red, green and blue scaled images stacked on top of each other. Since all the visible images are became combination of the 3 main color, RGB images are referred as real-life images.

RGB image is represents each pixel in an array with 3 value. This values can be in range 0 to 255 (total 256 shades) in 'uint8' in 8 bit representation and can take value in range 0 to 65535 in 'uint16' 16 bit representation. In 'uint8' representation array (255,0,0) means red pixel array, (0,255,0) green pixel and (0,0,255) represents blue pixel in images. All the remaining combinations and bit values are the shades of this 3 component and varies according to the image.

In our project, RGB images taken as an output of the thermal camera images which represents the radiating heat waves from objects. This waves represented with red scale in warmer points and blue scale in colder points on object/objects with different values depending on the heat condition.

Since RGB colored images has 3 channel information, it's introduce a great flexibility in order to apply image processing techniques. Since RGB composed of 3 main color bits, it's carry on more information about image and provides us to have more sensitive and detailed classification.

As a potential disadvantages to mentioned benefits. Since RGB images carries more information about image, it may takes vastly memory space that may return costly in project. Also since the RGB image has 3 channeled information, this increase the workload during image processing.

All the remaining parts are in the same as mentioned method 1.

7 PRELIMINARY DESIGN

From the methods we explained in the previous section, we choose Method 1 as our main method. Many reasons were effective in choosing this method.

We took all our records in grayscale with a thermal camera for collecting data. One of the main benefits is that this technique can reduce the amount of data required to store an image. So, this can make it faster and more efficient to process and analyze. Also, grayscale has a one channel of information opposite the RGB which has three channel for information. This helps shorten the processing time and improves the algorithm.

In addition, by fixing the minimum and maximum temperature values in these records, we increased the accuracy rate in all records. The camera will not be able to dynamically update the maximum temperature value and the maximum value in the obtained records. It has been decided as a result of many tests that the minimum temperature value of this value is 15 and the maximum is 45 degrees. Grayscale is a range of gray shades from white to black. White is representing maximum value and black is representing a minimum value. The blackest value in the resulting records will show 15 degrees, and the whitest will show a maximum of 45 degrees.

To process the data, we will examine each frame one by one and apply some filters to these frames. Because each frame contains noise. Reducing these noises will increase the accuracy of the data we obtain.

It was thought that the Gaussian Filter would be better to reduce the noise in the frames. Gaussian Filters can effectively reduce noise and smooth images, which can improve the visual quality and clarity of the image. This filter make the result more accurate to reduce the noise in frame.

In addition, a common Region of Interest (ROI) has been determined for each record. This is because the region of interest does not change from material to material. This will reduce the computation time for each record and speed up the algorithm.

Then, a result was reached by taking the average of the ROI.

Our preliminary design results are represented as a graph in Figure 7. In the graph vertical axis is scaled with frames and the horizontal axis is scaled with pixel values on gray-scaled frames. Our first preliminary data-collecting design is structured on 3 subjects that is metal, plastic, and carton. All subjects have been tested for the first 10 seconds of heating by the heat source and after that 10 seconds of cooling in a room temperature environment. Each subject's records has processed frame by frame with our image processing function. With the help of our function, each frame passed through Gaussian Filter. This filter is used for noise reduction on frames for obtaining better results. Each record is graphed after passing through these stages.

Each record information, record name, and data tag is stored in a pandas data frame. The resulting graph has been passed through certain filters to soften it. For this, the moving average filter is selected and Figure 7 shows the smoothed graph.

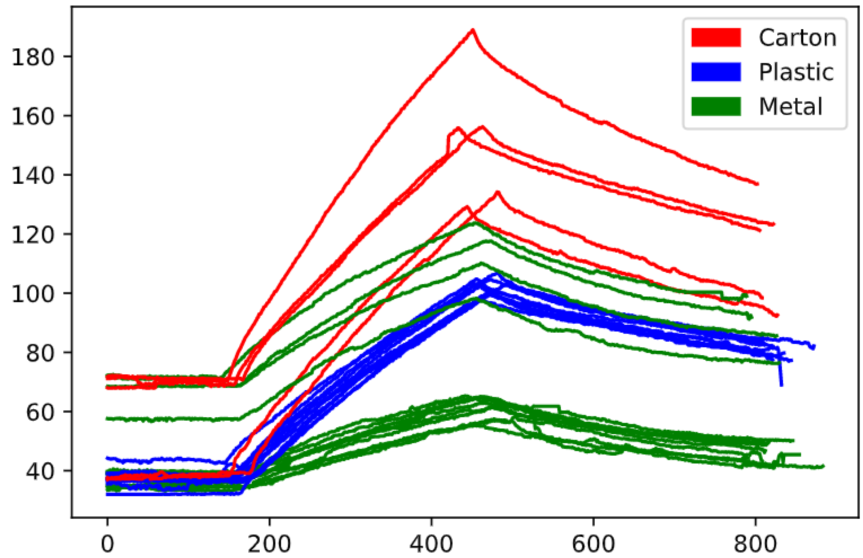

Figure 5 Data Frames

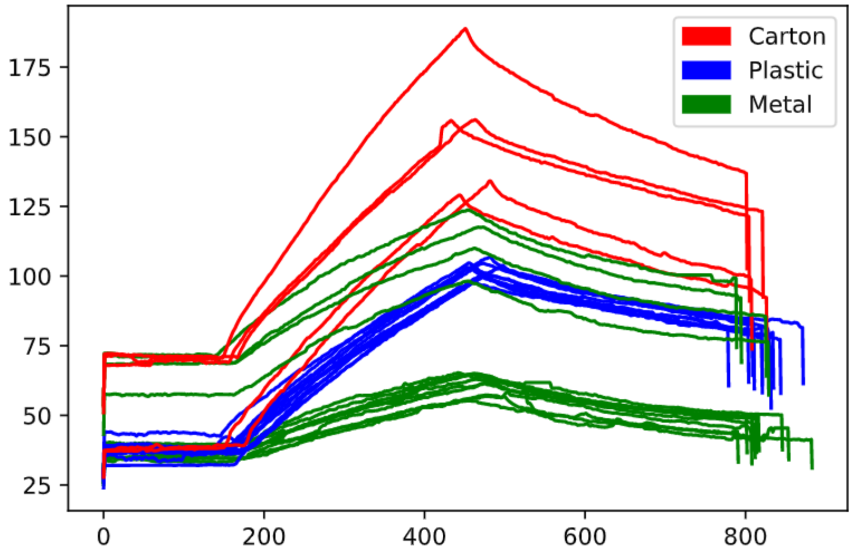

Figure 6 Filtered Data Frames

Our preliminary design shows that plastic and metal have very consistent data while the carton has inconsistency that may be caused by the test environment. Also noted that the metal has some inconsistency in some test results. These results belong to the same metal but were crushed before the test. The temperature value rise higher as the crushed metal bottle retained more light in it. These types of situations are noted and will be corrected in the upcoming designs.

Machine learning model:

After the data collecting part has been done, machine learning model will be created using collected data. For classification of this data, SVM (support vector machine) model will be used. SVM models are set of supervised training algorithm used for classification and regression[14]. Basically SVM model, creates a hyperplane or set of hyper planes in order to classify or separate our data in highest margins.

8 PROTOTYPE

The purpose of building the prototype for our project is to develop an efficient and accurate method for classifying waste materials based on their thermal characteristics. This will be achieved through a combination of hardware and software components, including a heat source, a thermal camera, and a computer for data processing and deep learning model implementation.

The prototype has been designed to:

- Heat objects to reveal their thermal characteristics.
- Record and process the thermal information using a thermal camera.
- Analyze the data with a deep learning model to classify objects based on their thermal properties.

Key features of the prototype include:

Heating Source: We used Osram brand 100W R80 lamps as a heating source to stimulate the waste materials. The lamps are positioned at a specific distance and angle during the data collection process to ensure accurate and consistent results.

Thermal Camera: A FLIR T-420 thermal camera with a 320x240 pixel resolution and a maximum frame rate of 30 FPS is utilized to observe infrared radiations of objects during the heating and cooling process. The single-channel images captured by the camera are color-mapped to produce sharper, more detailed images.

Data Processing and Deep Learning: Recorded thermal data is transferred to a computer where image processing techniques are applied, and a deep learning model is implemented for object classification. The process consists of three parts: data acquisition, data processing, and training, testing, and evaluating the deep learning classifiers.

Fig 7 : Prototype of Setup

Figure 2.1 provides an overview of the prototype setup, illustrating the heat lamps, thermal camera, and computer used for data processing and deep learning model implementation.

The experimental procedure is divided into three main sections: data acquisition, data processing, and training, testing, and evaluating the deep learning classifiers. In the data acquisition section, heat lamps are turned on for a specific amount of time (e.g., 5, 10, 15 seconds) to stimulate the object. Subsequently, the object is left to cool for a specific amount of time (e.g., 5, 10, 15 seconds) without any active cooling. The entire heating and cooling cycle is recorded using the thermal camera.

In the data processing section, image processing techniques are applied to the gathered video footage, processing the images appropriately. Algorithms are utilized to extract thermal characteristic information from the data, which is then used to train, test, and evaluate the deep learning classifiers for object classification based on their thermal properties.

9 DESIGN PROCESS

In this section, present the steps of the design process performed in constructing the prototype. The engineering design process is a series of steps that engineers follow to solve a design problem, and often involves an iterative process. Iteration is, in general, defined as the act of repeating something over and over again to improve the process and eventually achieve a desired goal. In a typical design loop, *first* a solution is generated, *second* the solution is implemented, and *third* the result of the implementation is tested and evaluated. If the results do not satisfy the requirements, additional solutions are generated and the above three-step process starts over again. This cycle and iteration continue until satisfactory results are obtained and the desired goal is achieved. An example flow chart that shows the design process is given in Fig. 1.

In the following subsections, discuss how the design is modified in each iteration by providing and evaluating the results obtained during testing, including difficulties encountered and new solutions proposed.

9.1 ITERATION 1

After completing the data collection phase described in the prototype section, a machine learning model is created using the collected data. The SVM (Support Vector Machine) model is employed for the classification of this data. SVM models are a set of supervised training algorithms used for classification and regression . Fundamentally, the SVM model creates a hyperplane or a set of hyperplanes to classify or separate the data with the highest margins. This approach ensures that the classification of waste materials based on their thermal characteristics is both accurate and efficient.

Before feeding the SVM model, feature extraction is required. This process enhances the performance, efficiency, and accuracy of machine learning algorithms by reducing the dimensionality of the dataset and minimizing the noise caused by irrelevant or redundant features. To achieve this, for each video frame from the collected data, we added every $\boldsymbol{i - 2^n}$ frame into an array, where n is the frame number and x is the amount of backing. In the first iteration of the code, we selected x as 8, resulting in the inclusion of ***i - (1, 2, 4, 8, 16, 32, 64, 128)*** frames combined to create our feature matrix.

This feature matrix is then fed into our SVM model to establish input-output relationships and make accurate predictions about subsequent data. By refining the feature extraction process and adapting it to the complexities of real-life waste materials, the SVM model becomes a powerful tool for classifying and separating waste based on their thermal characteristics.

9.1.1 TESTING AND RESULTS

To evaluate the performance of our feature extraction and prepare the data for our model, we utilized the scikit-learn library to obtain train and test values that would later be used to create our SVM model. These train and test values were fitted into the model to generate the SVM classifier. Once the SVM model was established, we tested its performance by feeding it one of the feature-extracted data sets from the earlier feature extraction phase. This data set was not used during the creation of the SVM model. Our data consists of three different groups: Metal, Plastic, and Carton.

In the first iteration and model, we opted for relatively smoother and straighter objects, which are not necessarily representative of real-life situations. However, this approach enabled us to develop a more effective model that could later be refined for more complex scenarios.

The results for the first model and preliminary data are as follows:

Test Material	Prediction Result	Accuracy
Metal 1	Metal	97%
Metal 2	Metal	88%
Metal 3	Metal	87%
Plastic 1	Plastic	83%
Plastic 2	Plastic	98%
Plastic 3	Plastic	93%
Carton 1	Carton	94%
Carton 2	Carton	87%

Figure 8 prediction results

While the initial results were encouraging, they did not accurately reflect real-life situations and required further refinement to handle more complex data. These improvements will be addressed in the subsequent sections of the project.

9.1.2 EVALUATION

Our first design created mainly considering regular shaped objects and the shows strength when testing it for that type of situation. But at the start, our main object has been the identifying the munipicial wastes which is mainly occurred with irregular shaped objects. So as expected our current algorithm will lack of evaluating that type of objects.

One potential weakness of the design when using irregularly shaped objects lies in the feature extraction process. In the current approach, the feature extraction is based on the inclusion of specific frames using the formula $i - 2^n$, which might not be able to capture the unique thermal characteristics of irregularly shaped objects effectively. These objects could have varying heat distribution patterns and cooling rates, which may not be accurately represented in the selected frames.

Additionally, the SVM model's performance can be affected by the complexity and variety of the waste materials. Irregular shapes may introduce more variability in the thermal characteristics, making it harder for the SVM model to create a clear boundary between different material classes. This may lead to reduced classification accuracy and efficiency when dealing with real-life waste materials that come in diverse shapes and sizes.

To address this issue, the feature extraction process may need to be refined and tailored to better capture the thermal characteristics of irregularly shaped objects. This could involve incorporating additional features or using more sophisticated techniques to account for the complex heat distribution and cooling patterns. Furthermore, exploring other machine learning algorithms or incorporating deep learning techniques could potentially improve the model's performance in handling the complexities of real-life waste materials with irregular shapes.

Also while we are collecting the data, we considered the region of interest in thermal footages according to the regular shaped objects which may cause a problem in irregular, squashed, smashed objects. We will address this issue again in iteration 2 part.

9.2 ITERATION 2

Our first design yielded successful results. Under these results, we wanted to test our algorithm with more data. We added various types of metal cardboard and plastic to this dataset. Care was taken to ensure that these objects did not have a smooth surface. It also allowed the algorithm to determine a dynamic ROI. This ROI was adjusted to vary depending on the size of the object.

Increasing the number of available data in terms of both variety and number was important in terms of testing the algorithm, and this greatly affected our algorithm in the final stage. The fact that the ROI can be determined dynamically with the data allows any object to be used during recording.

9.2.1 TESTING AND RESULTS

We have diversified the obtained data. A data group was created with metal cardboard and plastic objects with various surfaces, various numbers of data. The algorithm was trained with all the data collected in the 1st period. All data collected during this period were filtered through a preliminary examination. The algorithm was tested with all of the 2nd period data.

The result when we examine all the data:

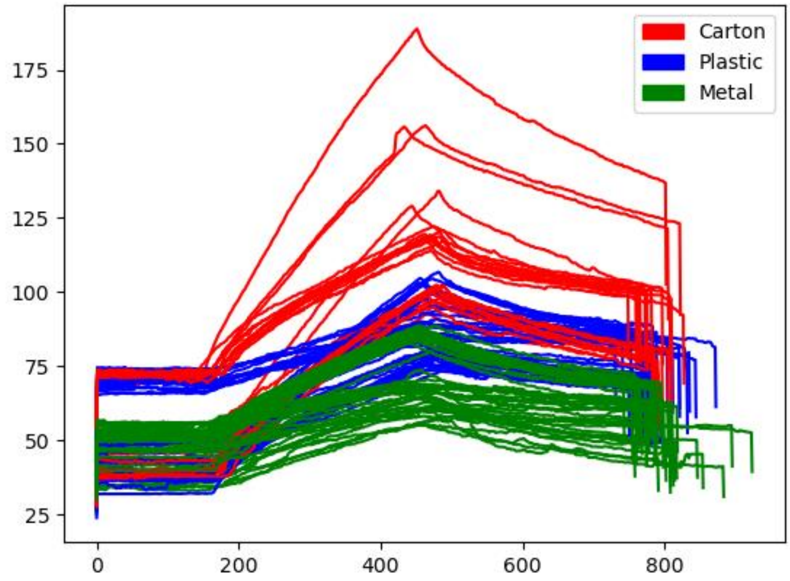

Fig 9 : Graph of dataset

Looking at the above result, unfortunately, we could not see a result similar to our first result. We think that the large number of objects in the data set and the fact that these objects do not have a smooth surface affect this graph. The reflections caused by these surface defects affected our graphics.

The algorithm, which was trained with the data set obtained in the first period, was tested with the data sets obtained in the second period. First, let's remember the methods again.

In our final report, we evaluated the results with 3 methods. These ;

Method 1 : $F[i] = X[i] - X[i - N]$ $\qquad N : 1, 2, 3, 4, 5, \ldots\ldots, n$

Method 2 : $F[i] = X[i] - X[i - 2N]$ $\qquad N : 1, 2, 3, 4, 5, \ldots\ldots, n$

Method 3 : $F[i] = X[i] - X[i - 2^N]$ $\qquad N : 1, 2, 3, 4, 5, \ldots\ldots, n$

While evaluating the results of the data we have, we will evaluate the 2 most successful of these methods. These methods is second and third method.

Here's the result :

Object Type	Method 2	Method 3
Metal	%75	%78
Carton	%39	%34
Plastic	%0.01	%0.1

9.2.2 EVALUATION

We expected the prediction percentage of 3 objects to decrease. Because we have both diversified and increased the dataset we have. All these data include some noise, some unexpected camera situations, some light reflections caused by the environment. In addition, the objects in the data set do not have smooth surfaces. So we were waiting for the results to decrease and we have some solutions to fix this and we are actively working on them.

One of the interesting results that emerged was that our algorithm never correctly predicted the plastic object. The reason for this is that the data set does not have a separation as we can see in the graph. For this, we think that all the data set we have should be reviewed again. All these data will be graphed again and the separation will be observed. If necessary, we suggest updating some data based on this observation. From the results discussed above, This is an expected result since the emissivity of metal is the highest and the carton is the lowest. Emissivity of plastic is in between so it is expected to be misclassified.

Although our machine learning algorithm gave very successful results, it was inefficient in some conditions. As we mentioned in our first term Final term report, we will add Deep Learning to our algorithm. We mention about these parts in next sections.

We will make corrections in our algorithm according to some of the weaknesses that emerged in this report and according to the feedback we receive from the machine learning algorithm. In our Deep Learning algorithm, we will use the first term data set and some new data for Train Set. This set will allow our algorithm to make the right decision in cases where it is undecided to increase the prediction percentage. At the same time, we are thinking of optimizing our algorithm by doing some tests on the hidden layer in the Deep Learning algorithm.

10 FINAL DESIGN

In final design, we kept all previous methods and design constraints constant. We paid more attention to increase the number of data we have and re-examined all the data we have. As a result of this review, we decided to enlarge the ROI a little more. As we mentioned before, we completed our Deep Learning algorithm in the final design and we got successful results.

Let's briefly review the whole design again.

Data Collecting and Processing

We used Method 1 while performing this design. Because thermal videos are collected in grayscale in phase of data collecting, since RGB images does not bring any further information. Also it is easier to store and process the grayscale images. Then temperature of the objects are inferred using the average temperature in a Region Of Interest (ROI) in the video. ROI is selected so that it covers most of the object. Having a decent ROI enable us to have more nuanced and accurate understanding of the data.

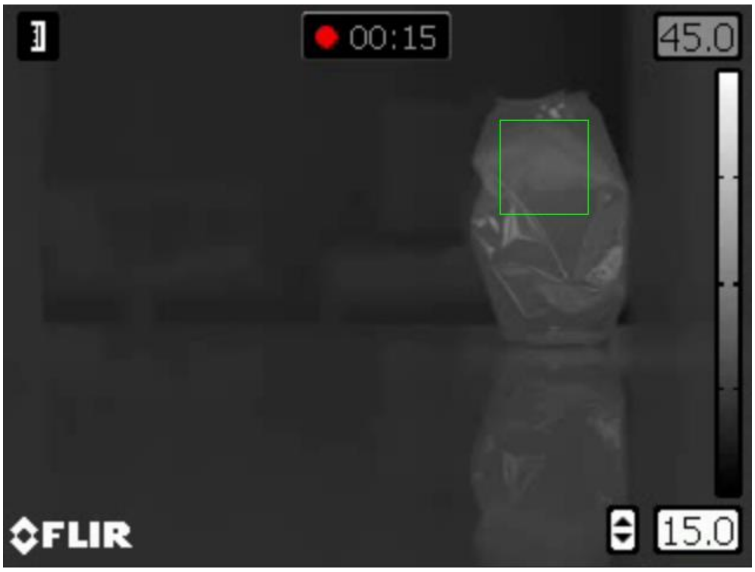

Figure 10 : Temperature readings are obtained by averaging the pixel values within the green rectangle.

After obtaining average pixel intensity value within the ROI in each frame of the video, a low pass filter, Hann filter is applied with window size 5. The aim is to remove the noise in obtained time series. At the end of this process, a time series that shows pixel intensity over time is obtained.

The resulting data has a length of 25 seconds, and each data has a 5 second initial display, a 10 second heating period, and a 10 second cooling period. Our camera, from which we obtain thermal images, records as 30 FPS as mentioned before. A point is selected to find the features. This point was chosen as the point measured as having the highest temperature average of the studied region. This point was chosen deliberately because the left and right sides of that point are separated into the warming and cooling processes. 150 points on the left and right sides of the point with the maximum temperature average of each obtained data were examined. 150 dots equals 5 seconds. In other words, 5 seconds were examined from the heating and cooling zones.

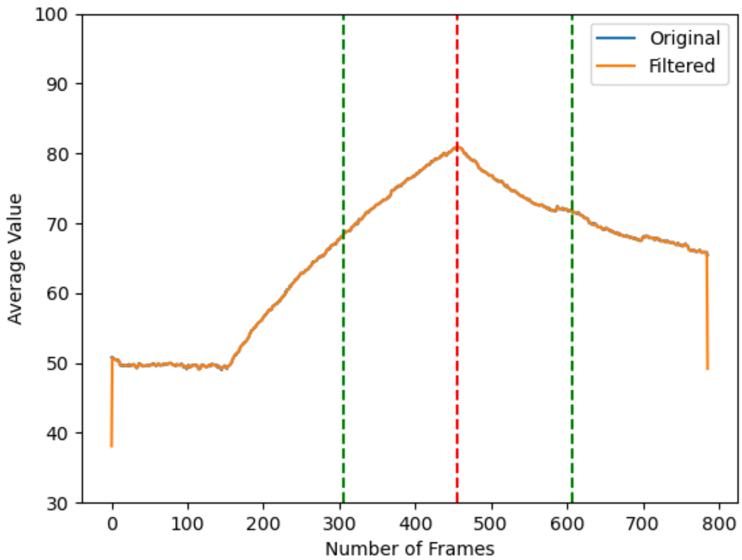

Figure 11 : Temperature over readings as object is subject to mentioned process

The vertical red line corresponds to the point where the temperature is the highest. Green vertical lines are 150 points away from it. So features are extracted from points between green vertical lines. In total features are extracted from 300 points. In order to obtain features, different feature extraction methods are used. Features are designed so that they exploit the relationship between a specific point and points before it. You can see how we extract features from the following equations.

Method 1 : $F[i] = X[i] - X[i - N] \qquad N : 1, 2, 3, 4, 5, \ldots\ldots, n$

Method 2 : $F[i] = X[i] - X[i - 2N] \qquad N : 1, 2, 3, 4, 5, \ldots\ldots, n$

Method 3 : $F[i] = X[i] - X[i - 2^N] \qquad N : 0, 1, 2, 3, 4, 5, \ldots\ldots, n$

Comparing all three methods, it is found that Method 3 is the best performing one and n is chosen 7 in equation . Even though it is shorter, it captures the evolving patterns and relationships between the points better than others, ultimately increasing the accurate representation and classification of materials. Features are extracted from the time series mentioned in previous section. In order to extract the features from time series, the point where the temperature is highest is chosen.

Training Classifiers

Training a classifier with a supervised learning model necessitates the careful preparation of both the input data and the corresponding outputs prior to initiating the training process. This stage involves with feature extraction, which sets the foundation for accurate classification. In this context, the output array has been made by using the label encoding method. This encoding method is applicable not only to the Support Vector Machine (SVM) model but also to a broad range of machine learning algorithms. The label encoding method assigns an appropriate integer to each distinct class of input, thereby transforming categorical labels into a machine-readable format.
In our specific case, we have three classes, namely metal, plastic, and carton. For clarity and consistency, these classes are encoded as follows:

- Metal: 0
- Plastic: 1
- Carton: 2

Following the initial data preparation stage, the next crucial step is to shape the data appropriately for optimal performance within both machine learning classifiers and deep learning algorithms. The data obtained during the feature extraction stage must be transformed into a compatible shape for this purpose. Our strategy is to concatenate the data, thus preparing it for input into a 2D classifier.

As mentioned earlier during the feature extraction phase, for each video input, a set of 300 frames were selected, leading to a 3D array of shape (n, 300, p) for 'n' number of videos and 'p' number of features. Correspondingly, the output array is of shape (n, 300, c), where 'c' is the integer label for the respective sample (0 for metal, 1 for plastic, and 2 for carton). However, these 3D arrays cannot be directly input into the classifier, necessitating their transformation into 2D arrays. To resolve this issue, the input and output arrays were concatenated and reshaped into 2D arrays, resulting in an input array of shape (300*n, p) and an output array of shape (300*n, c).

The final crucial step prior to inputting these arrays into the classifier is shuffling. The purpose of this step is to avoid potential bias and overfitting, thereby enhancing the model's ability to generalize from the training data to unseen examples. Shuffling ensures that the sequence of data does not influence the model's learning, yielding more reliable and robust outcomes.

The above-mentioned procedures are designed to be applicable to the broad spectrum of machine learning algorithms. Alongside these traditional techniques, we decided to train a deep learning model for the sake of comparing the effectiveness of various classifiers. Despite the different nature of the deep learning model, most of the mentioned steps remain relevant with only slight modifications needed.

The model architecture consists of multiple layers of linear transformations and activation functions. These layers are sequentially arranged to process the input data and generate predictions. The choice of activation function, in this case, is the sigmoid function. The first layer is a linear transformation that takes the input data with a size of 8 and maps it to a hidden layer with 32 units. The sigmoid activation function is then applied to introduce non-linearity and enable the model to capture complex patterns in the data.

Subsequently, the second layer performs another linear transformation on the output of the previous layer, mapping it to a hidden layer with 64 units. This layer is also followed by a sigmoid activation function.

The pattern of alternating linear transformations and sigmoid activations continues with subsequent layers. The third layer maps the 64-dimensional hidden representation to a 256-dimensional space, the fourth layer maps it to a 512-dimensional space, and the fifth and final layer produces the output with a size of 3, corresponding to the three classes being predicted. This model has been adjusted and selected according to tests after several trials. You can see architecture of ANN.

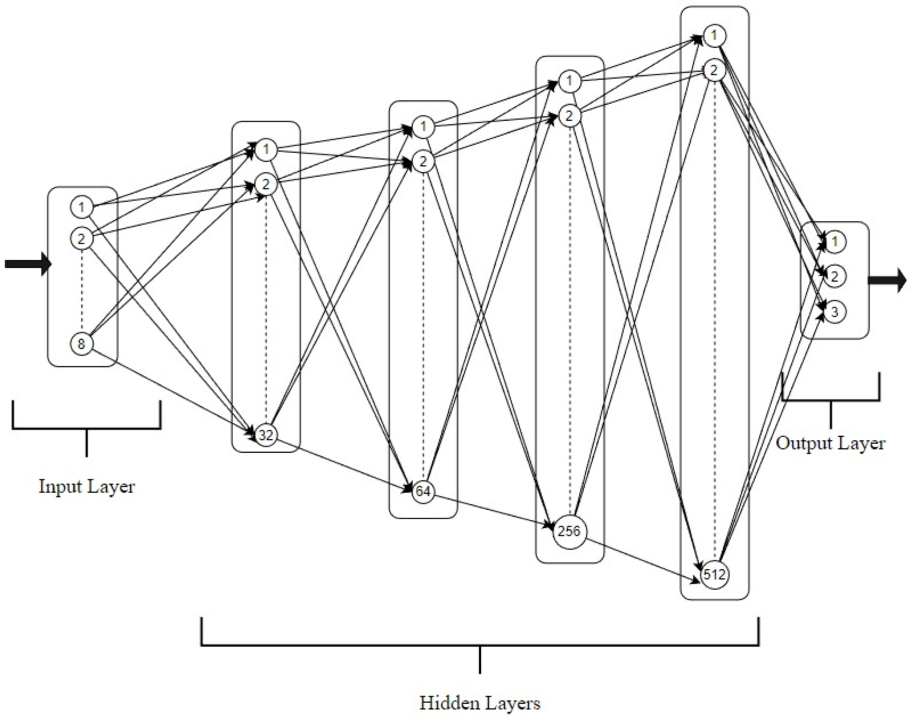

Figure 12: ANN architecture

Before diving into the specifics of the deep learning algorithm, it's important to highlight a crucial preprocessing change in how the subject's output is encoded. Unlike other instances where integer encoding may suffice, the context of deep learning necessitates the use of a one-hot encoding method.

This departure from is primarily dictated by the nature of the loss function adopted within our deep learning framework. The model makes use of Cross Entropy Loss, a common choice in this context that carries a specific requirement - it necessitates binary outputs for each input during the training phase in order to effectively compute the loss.

The reason behind this requirement is based on to how Cross Entropy Loss works. This loss function computes the divergence between the true distribution and the predicted distribution, and hence it requires binary outputs that represent a probability distribution across different classes. Thus, one-hot encoding is leveraged to transform our categorical target outputs into a binary format, rendering them compatible with the Cross Entropy Loss calculation, thereby facilitating a more seamless and efficient training process.

In the training process, Adam optimizer is used. You can see the behavior of loss and accuracy during training in Figure 10.4 and Figure 10.5 respectively.

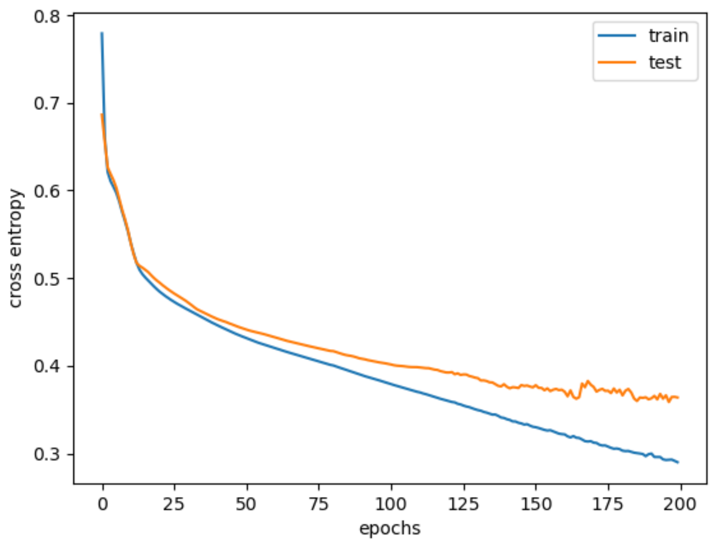

Figure 13: Cross Entropy Loss

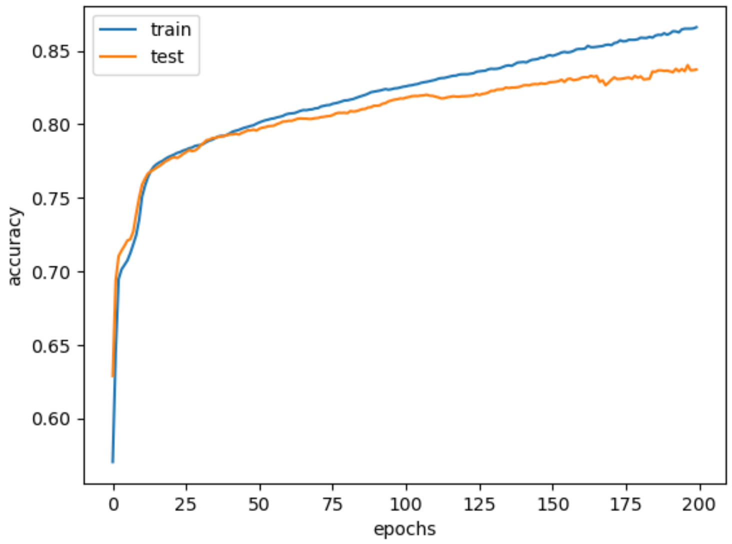

Figure 14: Accuracy Values

To determine the appropriate number of epochs for training, the model was trained up to a certain predetermined epoch number. The relationship between the training accuracy and the testing accuracy was then examined. The objective was to create a model that does not overfit, meaning it performs well on both the training data and unseen testing data. By analyzing this relationship, an epoch number was chosen to strike a balance between high accuracy on the training data and good generalization on the testing data.

Experimental Result

Before initiating the experiments, data were collected, features were extracted, and the models were trained as described above. To make better statement about this experiment its better to show it in terms of the result that obtained from each classifier. There are 6 different classifiers have been chosen. 5 of them were commonly used typical machine learning algorithms and deep learning algorithm.

- Support Vector Machine
- Decision Tree
- K Nearest Neighbors (KNN)
- Random Forest
- Gradiant Boosting
- Deep Learning

Classifiers mentioned in above are tested by using 30 time series (10 from each class) that are obtained from videos as described in section data collecting and processing. None of the time series used in testing is used for training. Their performance of each classifier is reported in Figure 10.6. It can be seen from the Figure 10.6 that k-NN performs the best while Decison Trees and ANN share the second place. Worst classifier appears to be SVM. Carton and metal classes are perfectly classified by all classifiers, while all the misclassifications happen in plastic.

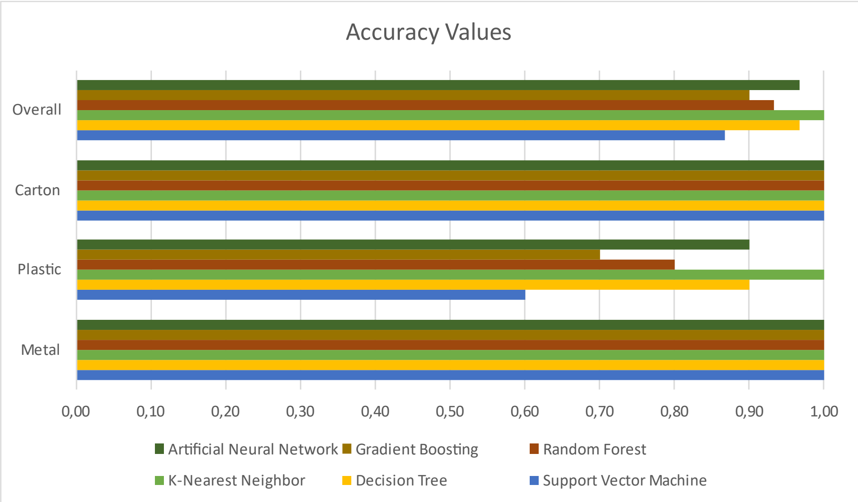

Figure 15 : Performance of Classifiers

Figure 10.7 demonstrates the predictions of all classifiers for all test set. As it can be seen from the table, plastic is mostly misclassified as metal. A plastic sample is misclassified as Carton in all classifiers but k-NN.

	Classifiers Predictions					
Samples	**Support Vector Machine**	**Decision Tree**	**K-Nearest Neighbor**	**Random Forest**	**Gradient Boosting**	**Artificial Neural Network**
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Metal	Metal	Metal	Metal	Metal	Metal	Metal
Plastic	Metal	Plastic	Plastic	Metal	Metal	Plastic
Plastic	Metal	Plastic	Plastic	Plastic	Metal	Plastic
Plastic	Plastic	Plastic	Plastic	Plastic	Plastic	Plastic
Plastic	Metal	Plastic	Plastic	Plastic	Plastic	Plastic
Plastic	Plastic	Plastic	Plastic	Plastic	Plastic	Plastic
Plastic	Plastic	Plastic	Plastic	Plastic	Plastic	Plastic
Plastic	Plastic	Plastic	Plastic	Plastic	Plastic	Plastic
Plastic	Plastic	Plastic	Plastic	Plastic	Plastic	Plastic
Plastic	Carton	Carton	Plastic	Carton	Carton	Carton
Plastic	Plastic	Plastic	Plastic	Plastic	Plastic	Plastic
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton
Carton	Carton	Carton	Carton	Carton	Carton	Carton

Figure 16: Classifiers Predictions Table

From the results discussed above, metal and carton classes are easiest to classify, while the hardest one is the plastic. This is an expected result since the heat capacity of metal is the highest and the carton is the lowest. Heat capacity of plastic is in between so it is expected to be misclassified.

10.1 MEETING THE CONSTRAINTS AND ENGINEERING STANDARDS

This project used the IEEE Standard for Artificial Intelligence (AI) Model Representation, Compression, Distribution, and Management [5].

This standard defines AI development interface, AI model interoperable representation, coding format, and model encapsulated format for efficient AI model inference, storage, distribution, and management. This standard provides efficient toolsets for inference, compression, decompression, coding, and packaging of the AI model that breaks down the AI model’s barriers between different computing architecture and algorithm frameworks, storage cost, as well as protects business sensitive information.

Our project is to classify waste object using thermal characteristic, some machine learning and artificial neural network algorithms. This standard is necessary because tools and algorithms for artificial intelligence and machine learning is widely used.

DESIGN CONSTRAINTS

- **Electromagnetic Radiation Issues**

In this project, A thermal camera is used to collect data. Thermal imaging is a method of using infrared radiation and thermal energy to gather information about objects, in order to formulate images of them, even in low visibility environments. Thermal imaging is based heat which is emitted from all objects. This energy from an object is also referred to as the “heat signature”, and the quantity of radiation emitted tends to be proportional to the overall heat of the object. The amount of radiation used by the thermal camera in imaging is harmless.

- **Budged Limitations**

The thermal camera (FLIR T-420) to be used in this project calibrates itself after a certain period of time. It needs be replaced but the budget limitations prevented it.This problem caused some minor issues during data collecting part. Because it was causing the distrapiton to the collected data. But this issue mostly overcomed by the filter we’ve used before feature extraction.Hence no harmed cause to the overall results.

- **Designs that help solve common international and national problems**

Waste is increasing day by day due to the rapid increase in the population of the world This situation contributes to increased environmental pollution and the depletion of earth's resources. That's why recycling is so important. Correct classification of waste is a time-consuming task in recycling. Our project is to classify waste object using thermal characteristic and some machine learning algorithms. This system is contactless and non-destructive, therefore it is suitable for a wide range of application scenarios.

- **Honesty, truthfulness, and openness in the design and the report**

In this project, we will share the design we made, the codes we will write and the report in an accurate and open source manner.

- **Designs that can be physically implemented**

Unfortunatelly we couldn’t manage to make phisically realizible system due to time and hardware limitaions.

- **Designs that support future upgrades**

The design that we will use to collect data in this project can be improved in the future and we want to realize this.

10.2 .COST ANALYSIS

This project mainly occurs with software hence it has been used very few hardware or related parts. The hardware we’ve used in this project mainly used in the data collecting part and there was no hardware on the final product. If we make list of the hardware and software we’ve used as follows:

- FLIR T-420 Camera: ~ 115,000 TL

https://www.aaatesters.com/flir-t420-thermal-imager-model-t-420-flir-420.html

- 3 Osram R80 heating lamps: ~450 TL

https://www.ampulmarket.net/r80-100w-e27-reflektor-osram

- Python programming language and related libraries: Free

So overall 115,450 TL is the budget of the project. But the important part is The main budget is the FLIR camera and it was provided us by our department. In addition, this thermal camera will be used on various new projects hence it’s wrong to be considered as cost of the project that much.

11 TEAM WORK

In this project, each group member had similar tasks to achieve finding a solution to a problem encountered during the 2 term we've been through. Our tasks were not strictly defined or separated because of the nature of the project. Our project was mainly based on software and computer programming so, we've been working on the same problem we've encountered with contacting and sharing the solution to each other. By doing that we were mastering the whole algorithm and getting more efficient solutions by sharing and arguing with each other.

12 COMMENTS AND CONCLUSIONS

In this project, an automatized solution to municipal waste management is proposed. Specifically, a comprehensive framework for automatized waste separation is introduced. The study convincingly demonstrates the effectiveness of utilizing thermography methods to classify objects based on their material composition, even in cases where the colors of the objects differ significantly.

The key premise underlying the proposed methodology is the inherent diversity of thermal characteristics exhibited by different materials. By leveraging this property, it becomes feasible to accurately categorize objects into their respective material types. For instance, metals, with their comparatively higher thermal capacity, can be reliably distinguished from carton or other materials. This approach opens up new avenues for streamlining waste separation processes, enabling more efficient recycling and disposal practices.

By offering an innovative framework and leveraging the power of thermography, this work presents a significant contribution to the field of municipal waste management. The proposed automated solution holds immense promise in revolutionizing waste separation processes, leading to enhanced resource recovery, reduced environmental impact, and more sustainable waste management practices overall.

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