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# Engineering Capstone

A low-cost, portable plastic identification device

REPORT BY
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# Abstract

Plastic recycling is a brilliant method of reducing the impact that plastic has on our natural environment, however it still suffers from many problems that stop it from being truly effective. A major issue is the expensive and inaccessible nature of plastic identification technology, which is necessary for separating polymer types and allowing the material to be recycled. Infrared Spectroscopy is the industry standard for identifying polymer types, however most of the technology has been designed for costly machines that process large volumes of plastic and is thus the technology tends to be out of the price range of small-medium scale recyclers. An open-source project 'The Plastic Scanner' is trying to solve this by utilising a cheaper method of 'Discrete Spectroscopy' paired with Machine Learning, however they have yet to develop a device with accuracy & reliability suitable for commercial use.

This capstone project seeks to further develop and improve on the work produced by The Plastic Scanner project, especially to overcome the PCB noise and accuracy problems that they are facing. This was achieved by developing a new version of the plastic scanner device, taking some of their proposed ideas and concepts but making new design and technical choices along the way. The device works by shining IR LEDs of very specific/discrete wavelengths of light onto a plastic sample. A differing amount of this light will be reflected depending on the type of plastic, which is then collected by a photodiode and converted to a digital value. In the Plastic Scanner project, there are 8 intensity data points collected, one for each LED in sequence. A novel improvement proposed in this report is to also shine the adjacent pairs of LEDs together. The light from these pairs superimpose, giving a new unique intensity value, resulting in a total 15 data points collected (8 original values, plus 7 new superimposed values). These values are then fed into a feed forward, supervised machine learning model that was trained on collected data from the device. The model suggests the most likely plastic, which is then output to a touchscreen display on the device. In total there were 2580 individual scans collected on over 500 plastic samples. The completed project from this report is a battery powered, portable handheld device capable of identifying HDPE, LDPE, PP, PET, PVC, PLA & PETG polymer types with a real-world accuracy of over 92%. The results found in this project represent a tremendous advancement in affordable plastic identification technology, which could prove beneficial to small-medium scale recyclers and allow for more plastic to be recycled and not end up in landfill.

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# 1 Introduction

Plastic is an increasingly pressing environmental concern in the modern world, as more plastic is being produced now than at any point in history *(Walker & Fequet, 2023).* Plastic recycling has shown the potential to solve this problem however, there are still several issues that need to be addressed before it can be truly effective. One particularly big issue is the expensive and inaccessible nature of plastic identification technology. Plastic identification is an integral part to the recycling process, as plastics need to be sorted into their polymer types before being recycled, otherwise the resultant plastic is of a poor and often unusable quality *(Jack, 2022).*

There are many different methods that can be used for identification of plastic types, which until recent decades mainly involved testing the plastics physical properties like melting temperature, density and solubility *(Zhu, et al. 2019)*. These methods are not only destructive, but also take considerable amounts of time and often lack accuracy. In the past few decades, Infrared (IR) Spectroscopy has emerged as the gold standard for identification in the recycling industry. This method identifies polymer type based on the IR reflectance off the material, which is fast, accurate and non-destructive but the technology can be quite expensive *(Zhu, et al. 2019)*. Due to this expensive nature, spectroscopy is mainly used for plastic identification in large industrial machines that sort vast amounts of material. Thus, there is very little to no affordable options of spectroscopic plastic identification for small to medium scale recyclers.

A promising solution to this gap in the market was proposed in a pre-print paper *(Straller & Gessler. 2019)*, which used the idea of “discrete spectroscopy” paired with a machine learning model in a handheld device to identify plastic types. The device they developed reached 95% accuracy across 4 types of plastic, however this was on an extremely small and non-diverse sample set. An open-source project, “The Plastic Scanner” was started as a way of continuing the work of Straller & Gessler and the project has made some great improvements, however they have yet to develop an all-in-one device with accuracy & reliability suitable for commercial use.

This report will outline the development of such a plastic scanner device and explore methods of how the accuracy and reliability can be improved to make it suitable for small to medium scale identification & recycling. The findings will be contributed back to the open-source project and community so that the technology can remain accessible and continue to improve over time.

*Figure 1: The completed device*

# 2 Literature Review

## 2.1 Existing Research

### *2.1.1 Conventional Spectroscopy*

Due to the well-documented effects that plastics have on the natural environment and the resultant increased push for more effective recycling, there are several research papers into methods of identifying plastic types. The most common identification method is certainly the use of Infrared Spectroscopy, which according to *(Zhu, et al. 2019)* is likely due to the technologies ability to be *"accurate, non-polluting, non-destructive, and the measuring is rapid without surface pretreatments".* The technology works by measuring the reflectance off a plastic object at different wavelengths of IR, which will produce a similar output to that of other plastic objects of the same type *(Angelin, et al. 2021)*. Due to the wide variety of plastic types and additives included within them, there has been the formation of two main IR ranges used for identification. Groups like *(Zhu, et al. 2019)*, *(Pakhomova, et al. 2020)*, *(Freitag, et al. 2000)* and *(Rani, et al. 2019)* all use a range of around 800-1700nm (Near IR), whereas *(Angelin, et al. 2021)*, *(Yan & Siesler. 2018)* & *(Unimaya, et al. 2023)* use a range around 1000-3000nm (Mid IR). These directly correspond to Infrared ranges offered by common off the shelf InGaAs (Indium Gallium Arsenide) detectors. As is shown in *(Crocombe. 2018)*, the Mid IR range tends to fair better for plastic identification compared to the devices that used Near IR. This is further supported in the spectrographs found in *(Becker, et al. 2017)* where the larger Mid IR range allowed for identification of black (carbon additive) plastics, which are otherwise unidentifiable using Near IR. The issue with Mid IR however, is that it is considerably more expensive, as again shown in *(Crocombe. 2018)* where Near IR devices are hundreds of dollars and Mid IR devices are thousands.

Despite the disparity in costing and suitability for identifying plastic types, Near IR based devices can still achieve suitably high identification accuracy by incorporating machine learning algorithms. This can be seen in *(Zhu, et al. 2019)* where they incorporate a "Support Vector Machine" to improve the accuracy of the device to an overall of 97.5% for PP, PS, PE, PMMA, ABS and PET plastics. Another quite common method of improving accuracy in these devices is Raman or Fourier Transform infrared spectroscopy, which is an analysis technique utilized alongside visual identification, as mentioned in *(Pakhomova, et al. 2020)*. However, they go on to say that "A common disadvantage of these methods is that they are expensive, require qualified staff and have to be placed in the laboratory and thus cannot be used in the field. " So, whilst this is a very common and effective way of increasing accuracy, it is not applicable to a handheld device.

### *2.1.2 Handheld Spectrometers*

As can be seen in the previous section, most of the literature on this topic centers around the science behind IR plastic identification, with little research into application. There are a couple of examples where research has been conducted specifically into the application of IR spectroscopy for handheld or portable devices. (Angelin, et al.2021) states how "Until very recently, handheld spectrometers were the domain of major analytical and security instrument companies" but now due to "low-cost visible-shortwave NIR instruments" there are capable and effective handheld instruments suited to "giving answers to non-scientist operators". (Angelin, et al.2021) and *(Yan & Siesler. 2018)* both conduct comparisons of off the shelf spectrometers capable of sensing spectra in the 1000-3000nm range, however these technologies are still very expensive.

A promising low-cost sensing solution is detailed in *(Straller & Gessler. 2019)*, with the proposal of a "handheld discrete spectrometer" for plastic identification. A discrete spectrometer is different from a traditional spectrometer, in that it only measures reflectance at a few points within a given range, rather than a continuous output. For example, *Straller & Gessler* only measures the reflectance at 7 points in range from 850-1650nm, which dramatically reduces the cost; and accuracy, compared to a traditional spectrometer. Similar to *(Zhu, et al. 2019)*, *Straller & Gessler* also use a machine learning model to evaluate the collected date and determine the most likely plastic type, with them being able to achieve 95% accuracy *(Straller & Gessler. 2019)*. However, this was only across 4 types of plastic and consisted of a very small sample set of less than 20 individual plastic samples. They mentioned that further research and development is needed for such a device to be viable, in particular improvements are needed for the signal processing and the amount of LEDs on the device.

## 2.2 Existing Solutions

There are a few handheld material/plastic identification products that are currently available on the market, notably the NIRvascan *(ASP Laser Inc, 2023)* and PlasTell devices *(Matoha, 2022)*. These products use conventional spectroscopy for their identification method and are thus quite expensive. The most reasonably priced option is the NIRvascan device which is based on the Texas Instrument NIRscan development module. This is a small, battery-operated device that uses optics and DLP technology to obtain an intensity over wavelength response of a given sample, however it does not output a material type based on this graph. This is likely due to this being targeted at scientific applications where such classification it is not entirely necessary or helpful to the user. Similarly, the PlasTell device is another handheld conventional spectroscopy device, however it is not battery operated and is thus not portable. Where the PlasTell has the advantage though is that is has been specifically designed to identify plastic polymers and will indicate this on a small screen after each scan. The identification is achieved by leveraging a custom-built machine learning model which comes pre-installed. This device is used in a reasonably number of recycling facilities, however the price is still quite high with it being 50% more than the NIRvascan.

Another existing solution is the previously mentioned open-source project the “Plastic Scanner” *(De Vos, 2023)*. This project was started with the goal of continuing the discrete spectroscopy work that Straller & Gessler (ReRe meter project) had outlined in their pre-print paper. The hope of the project’s coordinator is to develop an affordable plastic identification device and keep the technology open and accessible to all, so that it can have an even greater effect on the global plastic recycling issue. There have been a series of contributions by several individuals to this project, which has resulted in some good progress made on the device from Straller & Gessler. These contributions have been making the technology more reliable to work with, use more accessible componentry and added more plastic types that can be identified.

## 2.3 Impacts of Plastic & Plastic Identification Technology

Plastic has two major problems that it poses to the environment, its production and its disposal. Most plastic is produced from crude oil in a process that releases large amounts of green house gases into the environment. Plastic production is contributing about 3.3% of the global greenhouse gas emissions each year *(Ritchie & Roser, 2023)*. The problem with plastic disposal is that it breaks down extremely slowly, sometimes taking hundreds of years to break down into its fundamental components *(Jack, 2022)*. During this time “Micro Plastics” (very small pieces of plastic) are produced as the material wears, which can then contaminate soil & organisms along the entire food chain *(Lee et al., 2023)*. A build up of this micro plastic can alter bio-chemical processes or act as a medium for toxins. This means that every time plastic is littered or discarded to landfill, the plastic contamination issue continues to grow.

Recycling can help reduce the negative effects of both of these issues, as recycling reduces the need for production of new plastic, and it helps reduce the amount that ends up in our natural environment. However, as previously stated plastic recycling has its own issues, namely the need to identify plastic polymer types and sort them before the recycling process. Current sorting & identification technology is targeted for large industrial scale recycling which limits who is capable of helping solve the plastic pollution problem. Thus, the development of a cheaper and more accessible plastic identification technology could have a tremendously positive impact on both the environment and society.

# 3 Project Overview

## 3.1 Project Scope

The project that is being proposed is to develop a low cost, handheld device that is capable of reliably identifying common plastic types easily, quickly and with an accuracy of over 90%. The findings will be contributed back to the Plastic Scanner project, in order to continue the openness and accessibility of this technology. Depending on the level of success that is reached in this project, considerations for manufacturability and commercialisation may be taken into account.

This scope is very broad and will encompass many facets of engineering including mechanical, electronics, embedded systems and machine learning. To avoid underdelivering, the project will be split into distinct stages and utilise iterative prototyping during development. As the sensing/spectroscopy related systems are the most fundamental and important parts of this project, they will be prioritized. The full development plan is outlined in 3.3.

## 3.2 Aims & Objectives

- Develop a "Sensing" PCB with the necessary electronic components to test discrete spectroscopy measurements. The PCB should be able to communicate with a microcontroller using less than 8 wires and it should have a signal-to-noise ratio of less than 1%.
- Develop a machine learning model capable of classifying plastic types based on discrete spectroscopic measurements. Accuracy should be over 90%
- Develop methods and designs of incorporating the previous objectives into a handheld device. In particular it should be comfortable to hold, have a LCD screen to act output for the device and have a battery life of at least 2 hours.
- Throughout the development process, cost of parts or manufacturing should always be taken into account.

## 3.3 Timeline & Milestones

1. **Concept Formulation**
    a. Background research and literature review.
    b. Discuss possibilities with academic supervisors.
    c. Decide on the scope of the research.
2. **Explore Electronic & Machine Learning Requirements.**
    a. Experiment with off the shelf spectroscopic sensor.
    b. Research existing solutions and similar projects.
    c. Explore the machine learning approaches for classifying plastic types.
3. **Design & Develop Sensing PCB**
    a. Design & develop the PCB using accessible electronic components.
    b. Program & test the PCB.
    c. Iterate and continue to new prototypes as needed.
4. **Develop Suitable Machine Learning Model**
    a. Build a labelled dataset of plastic scans.
    b. Begin training a machine learning model on this data set.
    c. Continue to refine the model and the dataset to improve accuracy.
    d. Iterate and continue to new prototypes as needed.

5. **Design & Develop Components for Handheld Device**
    a. Select necessary components for a handheld device.
    b. Wire together and test the components.
    c. Design the device enclosure in CAD, accounting for all components.
    d. 3D print the enclosure.
    e. Iterate and continue to new prototypes as needed.
6. **Integrate**
    a. Assembly the mechanical and electronic components together.
7. **Final Testing & Refining of Solution**
    a. Develop a new Machine Learning Model with the new integrated device.
    b. Complete final testing of the device and model.

A full Gantt Chart is provided in *Appendix A.3*.

# 4 Methodology

## 4.1 Discrete Spectroscopy for Plastic Identification.

As mentioned previously, Discrete Spectroscopy is a recent technological development (2019) but through projects like the ReRe Meter and Plastic Scanner it has shown the potential to be suitable for plastic identification. However, in both of these a major concern was that only 8 data points was not enough to reach sufficiently high accuracy levels, as conventional spectroscopy has hundreds or more over the same spectral range. The issue of course is that the IR LEDs that enable the discrete data points are very expensive and there are only a few LED wavelengths available in the NIR 800-1700nm range that is commonly used. More LEDs could be added by acquiring LEDs above 1700nm; further into MIR, however as mentioned earlier this is much more expensive.

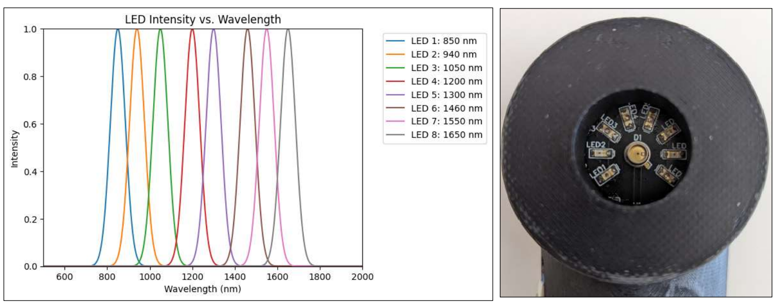


*Figure 2: (Left) 8 point discrete spectroscopy method. (Right) Device LEDs & photodiode layout.*

### 4.1.1 *Methods of increasing number of data points*

Having made this realisation, I begun to ideate other potential methods of increasing the amount of data points. An idea that did stick was to utilise superposition to gain extra data points from the same number of LEDs. The premise is to shine 2 LEDs with close wavelengths at the same time, allowing the light to slightly superimpose and give a unique intensity value. See the LEDs are labelled with the peak wavelength they emit, however they still produce small amounts of wavelengths around that peak. Because of this, the intensity measured by the photodiode is not of a single wavelength but rather the area under intensity/wavelength curve of each LED. Thus, if we had the same 8 LEDs that were used in the Plastic Scanner project but we shone adjacent LEDs together (1+2, 2+3…7+8 = 7 points) as well as each individually (8 points), we would end up with 15 total data points. Although purely theoretical, I considered it plausible enough that it was worthwhile experimenting with especially considering the alternative solutions were expensive and inaccessible.

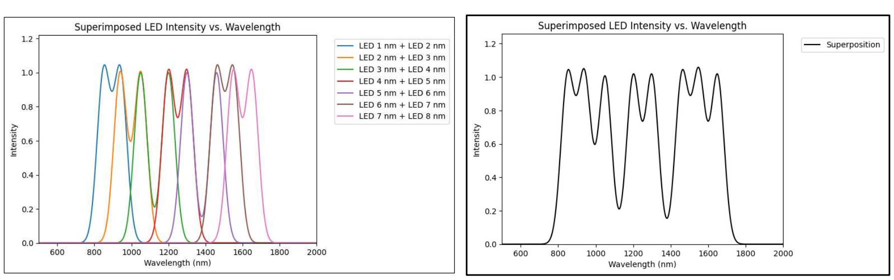


*Figure 3: (Left) 8+7-point discrete spectroscopy method. (Right) Full superposition response.*

## 4.2 Electronics Design & Development

The electronics development for this project was split up into different sections in order to prioritise the more important developments, but also to allow for modularity of the design. Because there are so many different aspects and unknowns in a project like this, modularity is a huge advantage as it simplifies things like debugging and makes it simple to swap out sections with an improved version. The electronics were split up into 3 main sections:

- Scanning PCB: Contains all the electronics components involved in obtaining spectroscopic values.
- Microcontroller: Contains the processing and power management side of the project.
- Peripherals: Contains things like the Touchscreen, buttons, switches and plugs.

### *4.2.1 Scanning PCB*

The scanning PCB was one of the most important systems that needed to be developments for this project, and thus demanded considerable time in order to complete. It is comprised of 3 subsystems which are responsible for the LED control, photodiode signal amplification and converting analogue signals to digital. The software that was used to design all of the PCBs for this project was EASY EDA, which is made by the PCB manufacturing company JLCPCB. The decision to go with this particular design software was made because I had previous experience using it and it has a large library of existing electronic components, complete with symbols and 3D models. Full schematics can be seen in *Appendix A.4*.

#### *4.2.1.1 Prototype 1 Board*

With the research into discrete spectroscopy completed, I began to design the first prototype for the scanning module. As this was my first attempt at such a complicated PCB design, I decided to focus on keeping the design simple by only including the necessary components, lots of debug probing points and having no considerations for space efficiency. Where possible, I wanted there to be a single communication protocol across all the electronic components, which in this case was $I^2C$ due to its abundance of components and simplicity of use.

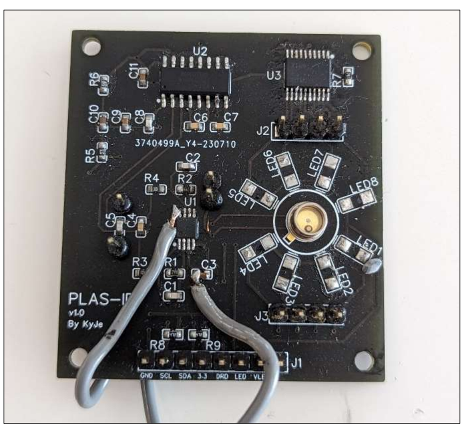


*Figure 4: The first custom PCB prototype*

*LED Control*

The design consideration I wanted to address foremost, was how to achieve the superimposing intensity method that I had theorised in the research stage. I needed a way of controlling the brightness of the LEDs, because if I simply turned two LEDs on at full brightness, I would likely saturate the OP Amp sensing circuit. I could decrease the amplification gain, however then I would be sacrificing resolution of the reading in the ADC circuit. After some searching, I came across the TLC59108IPWR Programmable PWM LED Driver by Texas Instruments. This is an 8-channel drain $I^2C$ LED driver capable of outputting an 8-bit programable brightness to any LED. With its max 120mA current output, this driver will easily allow 2 LEDs to be powered at one time and at whatever brightness value gets closest to max resolution without saturating. This driver also has an input resistor which allows easy control of amperage to all LED channels.

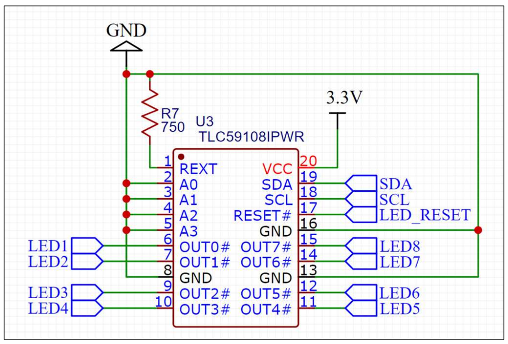


*Figure 5: 8ch PWM LED Driver Schematic*

*Photodiode Signal Amplification*

As mentioned previously, the most common type of IR photodiode that is used are made from InGaAs. As IR light hits the photodiode, a current is produced between its terminals which is proportional to the intensity of light. Both the ReRe meter and Plastic Scanner projects used an InGaAs photodiode, however they selected a Surface Mount Device (SMD) which has an extremely small active area of less than 0.075mm. The active area is the area that is photosensitive and it affects both the speed and accuracy of acquiring intensity values. The decision was made to go with a larger through hole InGaAs photodiode which had an active area of 0.25mm; 3 times bigger than the SMD component, and also has a cylindrical shroud around it to limit unwanted light being detected. Because of its larger active area this component is theoretically slower at reacting, however it is more accurate and reliable in its readings which is the main reason for the selection. It also had the added benefit of being cheaper and more accessible than the SMD equivalents.

Directly connected to the photodiode, there is a dual OP AMP IC with the photodiode terminals connected to each of the two inverting OP AMP inputs. This dual inverting amplification is also known as differential input and was proposed in both the ReRe meter project and later the Plastic Scanner project. It is a superior choice over a single differential amplifier design because it allows for “common mode rejection”, which effectively means noise/interference get cancelled out when you compare the two signals. Because of these advantages and its proven use case, I decided to follow the same design for my circuit, including the same components to achieve the same gain, as if this proved too low I could always easily change the passive components.

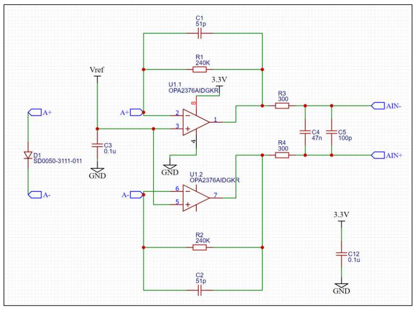


*Figure 6: Photodiode & Operational Amplifier Circuit*

An issue was encountered in this first prototype board related to the amplification circuit that both my board and the Plastic Scanner board where using. The problem was that 3.3V was both the reference and the power voltage for the OP AMPs, which means they were subjected to saturation as the signal was amplified into the 3.3V rail. To remedy this I made a cut in one of the board traces and soldered a wire to a 1.5V reference voltage. This was a temporary solution, but it solved the problem and also massively increased the gain achievable from the same setup.

*ADC*

With the signal now converted from a current to a voltage and amplified, it can be interpreted by an analogue to digital converter (ADC). Because the OP AMPs were setup in a dual inverting method, an ADC with differential capabilities is needed. As I went with the amplification circuit design used in the Plastic Scanner project, I decided to use the same ADC as well due to it already being perfectly suited to the problem. The IC is the 24bit NAU7802 differential ADC which has the ability to communicate over I2C, which is perfect as it means all IC's on the scanning module PCB will use the same communication protocol. The extremely high resolution of 24bit is also very well suited to the problem at hand as it means differences in plastic reflectance values can be easier to discern. Despite being 24bit the effective resolution is actually lower as this is a sign integer value (range is $-2^{23}$ to $+2^{23}$), and because the current from photodiode terminals only flows in one direction the ADC will only read positive values. The NAU7802 has a calibration command that will try and place the baseline around 0, which means the max effective resolution that can be achieved is the positive component which is 23bit. This is still a very large resolution that means light intensity can be placed on a range of 0 to 8,388,607.

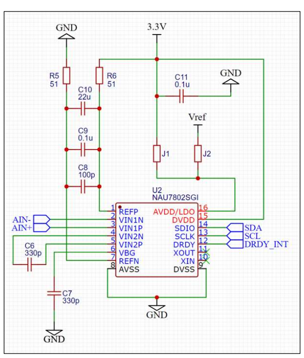


*Figure 7: 24bit Analogue to Digital Converter Circuit*

#### 4.2.1.2 *Prototype 2 Board*

The prototype 2 board largely used the same components as the first, however the layout was redesigned to make it more compact and there were a couple of changes to improve the boards accuracy and reliability.

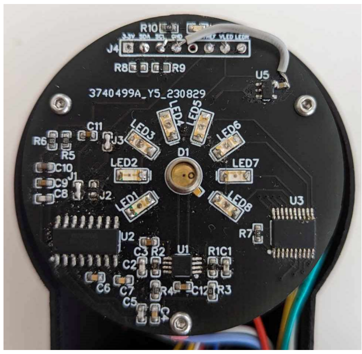

*Figure 8: The second custom PCB prototype*

*Circular PCB*

The decision to change to a circular PCB was made in order to make it simpler and more aesthetically pleasing. This also provided an opportunity to make the design more compact as this was neglected in the first prototype. It also has the added benefit of further increasing the signal integrity too, because lines between components where now much shorter.

*Removed Probing Pins*

Probing pins were initially incorporated into the design for testing and debugging purposes, however with the PCB working quite well they were now simply redundant and restricting the design from becoming more compact. Thus they were removed from the updated design.

*Added Decoupling Capacitors*

Although not a consistent issue, sometimes the power lines of the PCB were quite noisy, which would affect the accuracy of the scan data. I decided to add some decoupling capacitors close to the signal ICs which I had neglected to include in the first prototype, which should improve reliability even more.

*Added 1.5V Regulator for OP AMP Circuit*

Possibly one of the most important changes was to include a LDO (Low Drop Out) regulator IC on the board itself, as previously I had to rely on an external power supply to provide the newly appropriate 1.5V reference voltage to the OP AMPs and the IR LEDs.

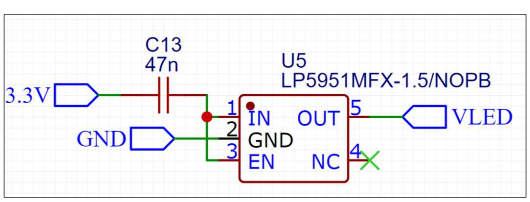


*Figure 9: Low-Dropout Regulator Circuit*

### 4.2.2 Processing & Power Electronics

With the scanner PCB developed, I now had to make a decision on the type of processing unit I should go with to control the handheld device. The main choice to be made is whether to go with a microprocessor or a microcontroller, which is effectively a choice between powerful processing vs smaller and more efficient computing. As the computational requirements for this project are not exceptionally high and it is supposed to be a portable device, I made the decision to go with a microcontroller as it provides enough power but in a compact and energy efficient manner. After some searching, I decided to use the Sparkfun Thing Plus C ESP-32 board which has an integrated LIPO battery charger and an SD card slot. This is an awesome device that will massively simplify development and integration as I can simply plug in a compatible LIPO battery and this ESP-32 board will be able to power the entire device. It also has the ability to charge the battery over the boards USB-C port. The SD card is a non-necessary; but nice to have, inclusion as it could be used to store scan data of plastic from field situations. This data can then be uploaded to a computer and labelled so it can be used in future datasets for the training of the machine learning model.

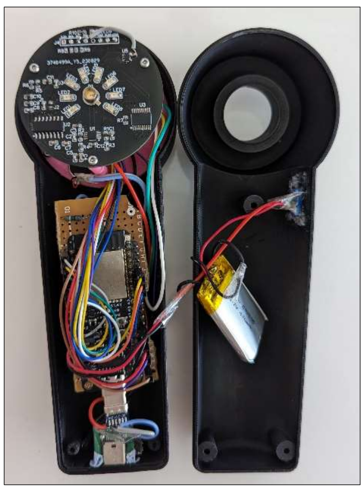

*Figure 10: Internals of completed device.*

### 4.2.3 Peripherals

To fully integrate all subsystems for this handheld device, there needs to be a couple of peripheral components added. These mainly have to do with user input and experience, namely methods of controlling the device, programming/communicating with it and powering it. A simple tactile push button was included as the main method of taking scans with a touch screen LCD screen being used as the method of display the data back to the user. Custom display outputs were developed in order to properly communicate the output prediction of the machine learning model, as can be seen below:

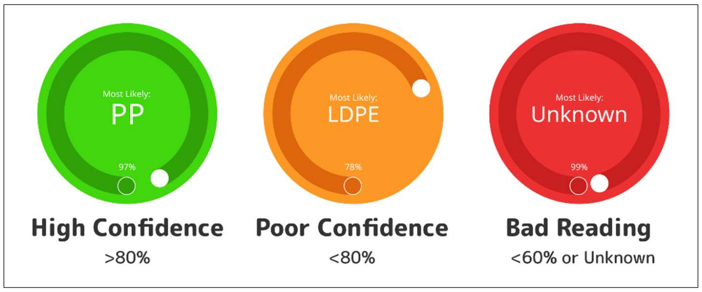


*Figure 11: The LCD output based on the ML models prediction.*

The touch screen was included with future proofing in mind, as it will allow the user to change settings or modes of the device making it far more practical and versatile. The final peripheral component was a USB-C breakout board which extends the microcontroller output to the bottom of the device enclosure. This allows the user easy access to programming the microcontroller with future updates and doubles as the method of charging the battery for the device.

## 4.3 Embedded Programming

The embedded programming was completed using VSCode as the IDE with the Platform IO extension, which is an open-source ecosystem for embedded development. C++ was the obviously choice of programming language due to its support and vast number of existing libraries for embedded systems. To simplify the development of the software, I decided to develop each sub-system separately and integrate them as libraries later down the line when they were working as expected. The structure of the code is outlined in the following flowchart.

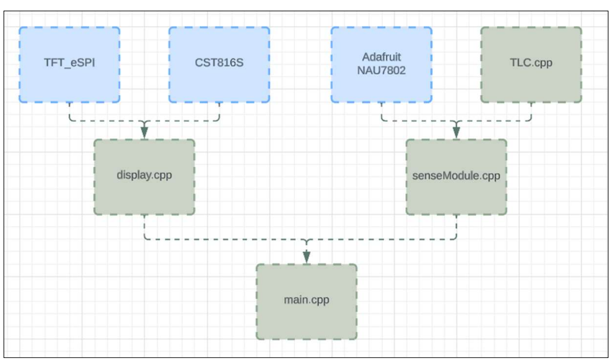


*Figure 12: Flow chart of embedded software files. Blue is external library. Green is self-developed library.*

With all of the libraries developed for each subsystem I could now work on the main file which would execute the high-level functionality of the device. For a flowchart of the high-level functionality please see *Appendix A.7*.

## 4.4 Mechanical Design & Manufacturing

With all of the electronic components developed and programmed, I could now begin the development of the mechanical structure of the device that would house all of this work. I first modelled all the electronic and peripheral components in Fusion360 to ensure that the enclosure will have sufficient space to fit everything. I then began to ideate and sketch out appropriate designs that would properly account for functionality, aesthetics and user experience. I settled on a design similar to one seen in the Plastic Scanner project. This was done because the design was aesthetic pleasing and functionally proven, but also to keep some commonality between my developments and the project I would contribute back to. The design was modelled with the intention to FDM 3D print it, as this is a quick and effective method of manufacturing non-structural prototypes such as this.

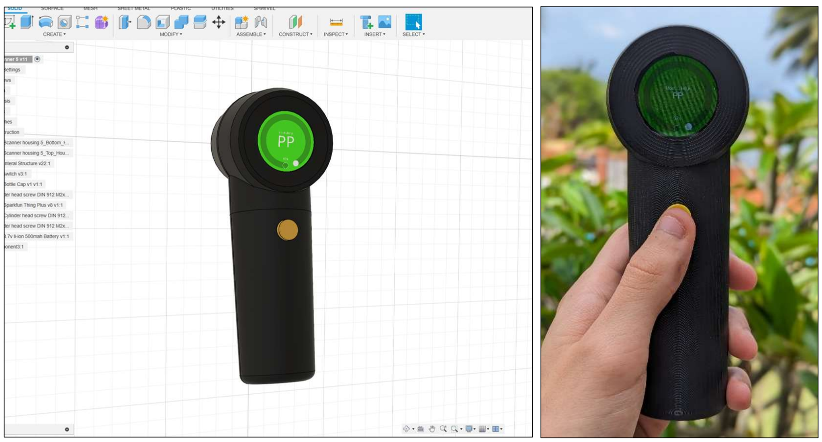


*Figure 13: (Left) Device modelled in Fusion360. (Right) Completed device outdoors.*

## 4.5 Data Collection

In order to develop a machine learning model, one must first develop a suitably sized dataset of high quality data which will be used for its training. For this, I enlisted the help of a local design and plastic recycling company by the name of Defy Designs, who supplied a large quantity of HDPE, LDPE, PP & PVC plastics. I also collected multiple household plastics to add to and further diversify the collection. With the plastics now obtained, I could connect the device to my computer over serial and recorded scan data. Due to this being a handheld device, there are many factors that can affect the values obtained, examples would be ambient light, background, distance the plastic is from the sensor, thickness of the plastic, shape of the plastic and any additives in the plastic. Because of these factors if one wants to achieve high accuracy across multiple plastic types, not only do you need diverse range of plastic samples but you also need a diverse range of scanning methods. When building out this dataset, I made sure to take multiple scans (on different faces of the plastic if applicable) of each type of plastic following these methods:

- Scan with aluminium as background
- Scan with hand as background
- Scan free-floating in ambient light
- Scan free-floating in low light

*Figure 14: Different methods of scanning plastics.*

These scanning methods should replicate the potential use in a practical application, which should improve the reliability and accuracy of the device. In the end I decided to have 8 categories that the ML model would identify which are HDPE, LDPE, PET, PETG, PLA, PP, PVC and Unknown. The unknown category was an accumulation of several different scanned objects such as wood, clothing, aluminium and also nothing at all. This was included so that the model would be able provide an output for things it thought weren't plastic. In total I collected 2580 unique scans of over 500 individual plastic pieces.

*Figure 15: Identifiable plastic samples. All 7 plastic types.*

## 4.6 Machine Learning

Now with a relatively large dataset obtained, I could begin developing/training the machine learning model. For this, I decided to use TensorFlow and python as these are some of the easiest & most popular solutions for training models from scratch. There was some extensive customisation and experimentation in developing the machine learning model particularly with the data used, model architecture, epochs and batch size. These variables often needed to be changed when there were changes to the amount or type of data used, as they affect the optimisation of the model.

I first started by training a model only including two types of plastic (PE & PP) and an unknown category, which was giving an acceptable accuracy of about ~88%. However, as I added more plastic types this accuracy would drop each time, ultimately with the 7 types of plastic all included the model was only capable of achieving an accuracy of ~78%. After some research I realised that these poor accuracies were likely down to the dataset being imbalanced, as I had not taken a similar numbers of scans for each category type. I decided to test the use of the SMOTE toolset to artificially balance the categories, increasing all of the lower numbered categories to the number of the largest one, which was ~400 samples. Doing this had a noticeable impact on accuracy, increasing the 3-category model to ~97% and the 7 category model to ~88%. Whilst very promising the 7-category accuracy was still too low from what the device needed to achieve, and I began to theorise that the dataset was still too small. Hesitant to sit down for several hours to collect even more scan data, I decided to test my theory utilising SMOTE to artificially increase the size. I arbitrarily chose a 5x increase in size, which resulted in the 7-category accuracy jumping to ~99%, with early stopping enabled and effectively zero noticeable overfitting this number is very high.

**Commented [KJ1]:** Fix this paragraph with updated model architecture and numbers

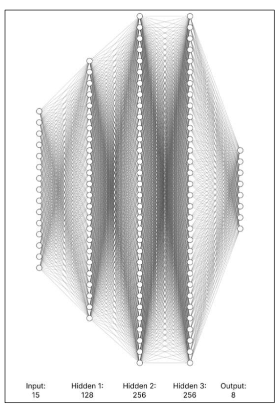


*Figure 16: Visualisation of the machine learning model architecture (Truncated).*

The above picture is of the final model that I developed. This model was compiled using optimizer Adam and loss sparse categorical cross entropy. Early stopping was enabled and a patience of 20 was set to allow the model to continue decreasing the loss. The max epoch was set to 500, using a batch size of 512 and a validation split of 20-to-80. This model was loaded in a python script on a host PC, from which it would receive scan data over Bluetooth from the ESP-32 in the device. The predicted plastic along with its confidence was then transmitted back to the device to be displayed. For more on the machine learning model and the code in general, please see *Appendix A.5 & A.7*.

# 5 Analysis of Results

## 5.1 Scanning PCB Accuracy & Reliability

### *5.1.1 Light Intensity Readings*

One of the most important requirements that needed to be met by this PCB, is for it to have very low noise so that it can provide more reliable and accurate scan data to the machine learning model. The subsystem responsible for this on the PCB, is the analogue sensing circuit comprised of the photodiode, OP Amp and ADC. To quantify the noise on the PCB, the device was placed firmly against a reflective surface and 5000 individual readings from the ADC were collected. This was done once with zero light (Dark) applied to the photodiode, and once with max light intensity. A relative ambient light reading was taken before each test and subtracted from each reading to normalise it for analysis. This data was collated, and the statistical results are as follows:

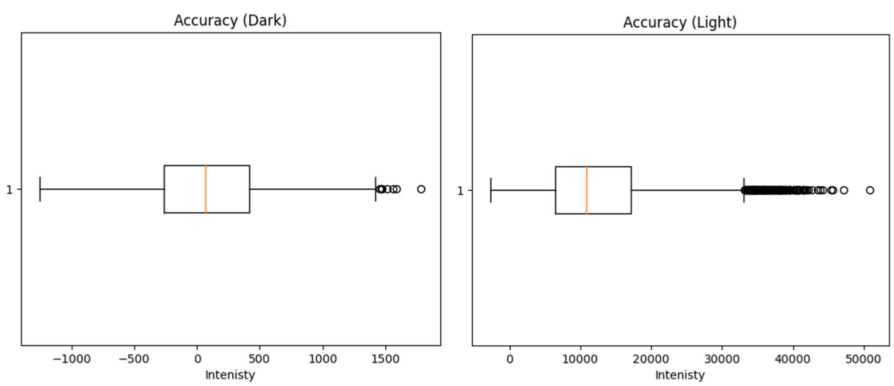


*Figure 17: ADC accuracy Boxplots.*

*NOTE: The negative Intensity/ADC readings are caused by noise and imperfect ADC calibration. Intensity value is from the ADC which ranges 0-$2^{23}$.*

| | Dark | Light |
|---|---|---|
| **Min Value** | -1252 | -2667 |
| **Max Value** | 1784 | 50847 |
| **Range** | 3036 | 53514 |
| **Median** | 66 | 10815 |
| **Mode** | 363 | 5811 |
| **Mean** | 76.89 | 12545.77 |
| **Q1** | -265.0 | 6440.75 |
| **Q2** | 66.0 | 10815.00 |
| **Q3** | 417.25 | 17105.25 |
| **Noise/Signal** | 0.0362% | 0.6379% |
| **Signal-Noise Ratio (dB)** | 14.4131 | 1.9525 |

*Table 1: ADC Dark vs Light accuracy.*

As can be seen in the above results, the PCB appears to have extremely low amplitude of noise in both cases. The test in the dark performed significantly better than the one in high light intensity, with the data inferring that as the light amount increases so does the noise.

It should be noted that even in the worst case (light) scenario, the PCB only ever has 0.64% noise peaks with 75% of scans being below 0.20% and an average of just 0.15%. This is a remarkably good result, and as can be seen later in the analysis it allows for the ML model to achieve very high accuracies. See *Appendix A.5* for the code used in this section.

### *5.1.2 LED & LED Driver Circuit Repeatability*

An important factor for the practicality and useability of this device, is how quickly it can scan a piece of plastic. Throughout early testing of the PCB I was having difficulty obtaining consistent values from the ADC. As the ADC was a ultra-low noise device and photodiodes tend to have response times in the nanoseconds or even picoseconds *(Wang, 2011)*, I theorised that the inconsistent values were due to the rise time (time to turn on) of the LED's. There was no rise time listed on the datasheet for the LED's I purchased so I decided to follow a similar approach to that of 5.1.1. I wrote a script that would shine an LED and read from the ADC, however it would iteratively increase a time delay in-between shining the light and reading its intensity.

| | **0ms** | **2ms** | **4ms** | **6ms** | **8ms** | **10ms** | **12ms** | **14ms** | **50ms** |
|---|---|---|---|---|---|---|---|---|---|
| LED0 | 699 | 2137 | 8349 | 483093 | 1590789 | 3012203 | 3021741 | 3036762 | 3086584 |
| LED1 | 1113 | 4523 | 20147 | 968089 | 3077575 | 5636621 | 5648551 | 5665668 | 5643822 |
| LED2 | 933 | 26623 | 87145 | 2168929 | 5497845 | 7043821 | 8384661 | 8388704 | 8388704 |
| LED3 | 1641 | 59181 | 171857 | 2826285 | 6224747 | 7528371 | 8388387 | 8339430 | 8388704 |
| LED4 | 4213 | 152701 | 358105 | 3701227 | 6868201 | 7880869 | 8388703 | 8371384 | 8388704 |
| LED5 | 397 | 423 | 586449 | 4494585 | 7366103 | 8099381 | 8185335 | 8385354 | 8388704 |
| LED6 | -27 | 617 | 509863 | 386013 | 1825411 | 4752421 | 4781001 | 4843522 | 4773050 |
| LED7 | 55 | 1787 | 458731 | 362063 | 1259879 | 2516153 | 2521517 | 2529680 | 2474056 |

*Table 2: LED response time.*

The above graph was the result of this experiment. As can be seen, a delay of at least 14ms is required in order for all LED's to reach 99% of their max intensity, with LED 5 being particularly slow. Implementing a delay of 15ms before every reading requested from the ADC, resulted in extremely consistent values. See *Appendix A.5* for the code used in this section.

## 5.2 Comparison of Identification Methods

The following 3 sections all use the same original dataset of 500 plastic items, totalling 2580 individual scans, however scan data not necessary for a particular sections model are selectively ignored. This was done to allow for the most valid comparison of the different models, with the only thing changing being the number of discrete measurements.

### 5.2.1 8-Point Discrete Method

The 8-point method follows the original approach proposed by the Straller & Gessler, where an intensity value is collected for each of the IR LEDs. In their pre-print paper, they had 7 LEDs and achieved an accuracy of 95% *(Straller & Gessler. 2019)* however, this was only a data set of 16 individual plastic items across PET, HDPE, PP & PS. In contrast, this 8-point method developed in this paper achieved an accuracy of 95.96% (0.12 loss) on a dataset of 2580 individual items and added LDPE, PVC, PLA & PETG plastics.

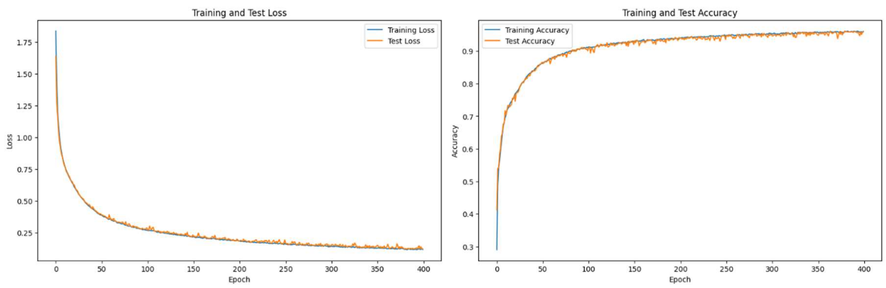


*Figure 18: 8-Point Discrete Method theoretical accuracy graphs.*

The above figures show the visualisation of this model, comparing the Loss and Accuracy for both the test and training datasets. As can be seen, there is extremely little, to no, overfitting with two methods following very close to one and other. Because SMOTE was used to drastically increase the size of the dataset, a large batch size of 512 was used, which resulted in very smooth and consistent training of the model.

### 5.2.2 8+7-Point Discrete Method

As mentioned earlier, this method is one that I theorised could be a suitable method of increasing the accuracy of the device without adding more LEDs or cost. This method includes the exact same 8 points from 5.2.1, however it adds 7 extra points to the data set by shining adjacent LEDs at half brightness to acquire intensity values. These values represent the intensity of the superimposed waves and similar to the other values should be unique to each plastic type. Using the exact same model architecture and values from 5.2.1 I trained a new machine learning model with these extra data points. The result from this was a model that achieved an accuracy of 99.37% and a loss of 0.02.

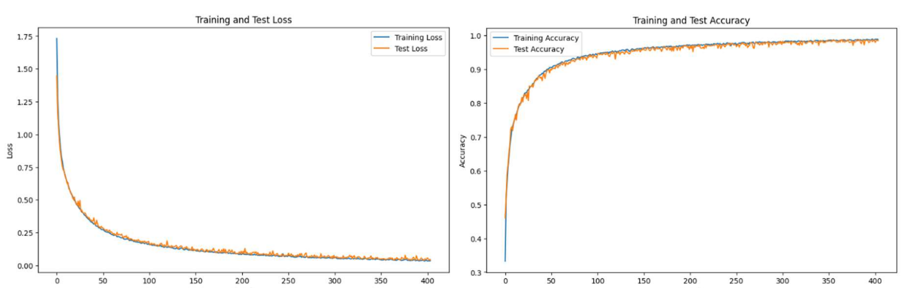


*Figure 19: 8+7-Point Discrete Method theoretical accuracy graphs.*

This is an amazing accuracy to achieve, especially considering this model uses the exact same architecture and hardware as that used in 5.2.1 but with an increase in accuracy of 3.43% (1-(95.96% / 99.37%). This is all whilst still effectively having no overfitting noticeable in the model visualisation seen above.

### *5.2.3 3+2-Point Discrete Method*

After seeing the benefits of utilising superimposed intensity values, I wanted to explore reducing the number of LEDs in order to decrease the cost of the device. Of course, the accuracy would be affected and any such device would be targeting a consumer market that cares less about extremely high accuracies and more about affordability. After testing different LED combinations I eventually settled on a model using 3 LEDs (850nm, 940nm, 1200nm) and their 2 corresponding superimposed intensities. These LEDs were selected as they were the cheapest, the exact cost savings are explored in 5.4.2. Because this model has far fewer data points per scan, it is not reasonable to assume that it could achieve an effective accuracy, so instead of the model classifying plastics into their polymer type it will instead make a binary choice between 'Unknown' and 'Recyclable Plastic'. The idea being that such a device could indicated if a plastic can be put into the yellow recycling bin or not, for this reason PCV, PLA and PETG were removed from the dataset as these are generally not recyclable in such a manner. With these changes made this model was able achieve an accuracy of 96.77% and a loss of 0.09. This was using mostly the same model architecture as the previous models, however with a lower batch size of 256 (due to their being less data points) and with a lower patience of 10 to help reduce over fitting.

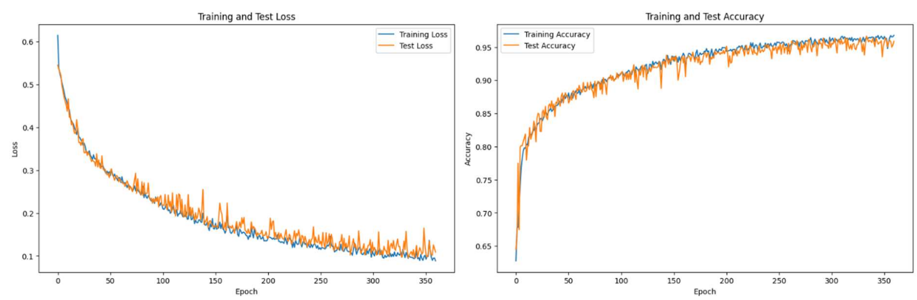


*Figure 20: 3-Point Discrete Method theoretical accuracy graphs.*

As can be seen above, this model is far noisier in its training and has some noticeable; yet acceptable, overfitting. This noise is likely due to the decrease in data points making it harder for the model to discern patterns in the data, as well as the fact that this reduction also increases the likelihood of outliers affecting the model. Despite this model performing worse than the previous ones, it shows the potential of such a significantly cheaper device is to be developed for consumer needs. See *Section 5.4* to compare the cost between the two devices.

## 5.3 Real World Testing & Accuracy

| | Predicted Label | Amount | Avg. Confidence | Correct Prediction |
|---|---|---|---|---|
| HDPE | HDPE | 44 | 97.90 | 88% |
| | LDPE | 5 | 90.71 | |
| | PP | 1 | 90.00 | |
| LDPE | HDPE | 6 | 64.50 | 86% |
| | LDPE | 43 | 94.72 | |
| | PP | 1 | 72.00 | |
| PP | HDPE | 1 | 74.00 | 96% |
| | PET | 1 | 91.00 | |
| | PP | 48 | 95.04 | |
| PET | HDPE | 1 | 99.00 | 92% |
| | PET | 46 | 97.84 | |
| | PLA | 1 | 99.00 | |
| | PVC | 2 | 94.33 | |
| PVC | PVC | 49 | 98.27 | 98% |
| | Unknown | 1 | 53.00 | |
| PLA | PLA | 49 | 97.84 | 98% |
| | PVC | 1 | 99.00 | |
| PETG | PETG | 46 | 96.89 | 92% |
| | PLA | 2 | 95.00 | |
| | PVC | 2 | 98.50 | |
| | | | Average Accuracy | 92.86% |

*Table 3: Real world device accuracy.*

To test the real-world accuracy of the device, 50 samples of each identifiable plastic type were collected, which were a mix of samples used to train the model and ones that it had never seen before. A scan was taken of each plastic sample and the predicted plastic type along with the confidence score was recorded. As can be seen from the above table, bar the PE plastic all plastic types had a real-world accuracy of over 90%, with the average being 92.86%. This is very acceptable accuracy for such a rudimentary prototype, especially one that tries to identify between HDPE & LDPE which are very hard differentiate. This device also only takes 2.5 seconds to identify a plastic sample, from button press to display output. Overall, this test provides further evidence that this device has the capability to be a functional and very useful tool in recycling environments.

*Figure 21: Completed device during testing.*

## 5.4 Cost

An important factor of this paper was to explore making a "low cost" device. This section will look at the cost for 2 proposed devices, an 8-LED high-accuracy focussed device, and a 3-LED affordability focussed device. The costs were calculated including all Consumer-Off-The-Shelf (COTS) components, PCB manufacture and PCB assembly for different quantity amounts. For full BOM, please see *Appendix A.2*.

**Device Cost (8-LED)**

| | Total Price | Price Per Device |
|---|---|---|
| Qty 5 | $1,104.55 | $220.91 |
| Qty 100 | $13,564.33 | $135.64 |
| Qty 1000 | $112,669.32 | $112.67 |

*Table 4: Device cost summary (8-LED).*

**Device Cost (3-LED)**

| | Total Price | Price Per Device |
|---|---|---|
| Qty 5 | $361.45 | $72.29 |
| Qty 100 | $4,447.33 | $44.47 |
| Qty 1000 | $36,429.32 | $36.43 |

*Table 5: Device cost summary (3-LED).*

As can be seen in the above tables, because IR LEDs are reasonably expensive, the 8-LED device is up to 3.09 times the cost of the 3-LED device. Despite this both proposed designs are a very viable, relatively cheap method for plastic identification, especially considering the cost of current options. The NIRvascan device costs US$2965 *(ASP Laser Inc, 2023)* and the PlasTell device costs US$3686 *(Matoha, 2022)*.

# 6 Difficulties & Recommendations

## 6.1 More Diverse & Larger Plastic Database

One of easiest ways of increasing the accuracy of the device is to continue building out an even more diverse and larger plastic database, complete with all scan data and labels. As can be seen in sections 4.6 & 5.2, a model trained on a much larger dataset is not only more accurate but also more reliable. Due to restrictions on time in this project, I had used SMOTE to artificially produce this larger dataset as it was not feasible to collect all that data myself, however it is almost certainly worthwhile to replace this with actual scan data. It would also be advantageous to continue adding more plastic polymer types to improve the capability of the device, as the more plastics that can be reliably identified the more valuable the device is.

## 6.2 TensorFlow Lite Integration

A major issue I faced towards the end of this project, was getting a functional TensorFlow Lite model working on the ESP32 microcontroller. The ESP32 Thing Plus C microcontroller I was using had plenty of memory (16MB) to run the TensorFlow model I had developed (400KB), however the device would always run into errors during run time. The main reason I wanted the model integrated onto the ESP32 was so that the device could be completely portable, with no wires. To achieve this for testing purposes, I simply communicated to the device over Bluetooth from a host PC. This is not always practical and thus getting the TensorFlow Lite model onto the device would be very worthwhile improvement. An alternative would be to use a small microcomputer like the Raspberry Pi

## 6.3 Further Research & Development of Cheaper 3 LED Device

*Section 5.2* outlined the 3+2-Point Discrete Identification Method, which is a method that could be used in an inexpensive 3 LED device to classify recyclable and non-recyclable plastics. This idea was only briefly explored in this project, with the graphs in *Section 5.2* showing how such a device could reach suitable accuracies for a consumer market. More careful collection of data as well as a more suitable machine learning model would be worthwhile avenues to explore to further develop such a device.

## 6.4 Microcontroller PCB

Due to the relatively short timeframe for this project, I did not see it prudent to prioritise the development of a custom microcontroller PCB when there were more important systems to complete. Instead, I opted to solder the ESP32 to some perf board and connect wires to the scanning PCB to this. This is far from optimal as it was not possible to properly secure such a solution to the 3D printed structure, and it has a proclivity to swish some of the wires. Given more time, developing a custom PCB would be a very advantageous improvement.

## 6.5 Larger Active-Area Photodiode

As mentioned in *Section 5.1.2*, one of the improvements I made on this device over the Straller & Gessler device was the use of a larger active-area photodiode. The photodiode I had has an active-area with a 0.25mm radius, however through testing it looks like even larger areas could easily be accommodated. Considering the device can already obtain the scan data very quickly, a photodiode with an active area of 1mm or 2mm radius could be used. This could further improve the accuracy and the reliability of the device, however with a slightly more expensive photodiode.

## 6.6 A Better Mechanical Structure

The mechanical structure and design for this project was of a much lower priority when compared to the electronics and software systems, and because of this the design is in need of several improvements. These include proper points to secure components, a more ergonomic handle, a protective cover over the scanning PCB hole and a round foam ring to improve surface contact with a plastic sample. Using a more advanced 3D printing technology such as SLS or injection moulding would be a worthwhile change over FDM 3D printing, as the layer lines and dimension inaccuracies are less than favourable.

# 7 Conclusion

This report has explored the development, testing and analysis of a low cost, portable discrete spectroscopy based plastic identification device. The finished device was capable of identifying 7 plastic polymer types, in less than 2.5 seconds and with a real-world accuracy of 92.86%. There were several specific novel improvements that led to achieving this successful device, in particular the 8+7-Point Identification Method, the proposal of an even cheaper 3-LED device, considerations for a handheld device and improving the signal-to-noise ratio of the scanning PCB. The findings of this report; along with all supporting documents and files, will be shared with the Plastic Scanner project so that this technology and device will continue to be developed in an open-source manner.

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# Appendix

## A.1 Communication Log

| | | | |
|---|---|---|---|
| **Project Title:** | A Low-Cost Handheld Device for Plastic Identification | | |
| **Student Name:** | Kyle Jewiss | **Supervisor Name:** | Sarath Kodagoda |
| **Date** | **Event** | **Topic of Communication** | **Outcome** |
| 8/3/2023 | Video Call | Project Introduction | Begin ideating. |
| 15/3/2023 | Video Call | Forming Research Question | We worked out a clearly defined research question together. |
| 22/3/2023 | Video Call | Discussed potential project components to purchase for testing | Conduct research and buy some components |
| 29/3/2023 | Video Call | Progress update and literature review discussion | Supervisor advised me to work on my literature review. |
| 5/4/2023 | Video Call | Progress update on how component testing is going | Got some software suggestions for some problems I was having |
| 19/4/2023 | Video Call | Discussed Machine Learning applications in the research | Look into the user of Tensor Flow Lite on a microcontroller |
| 3/5/2023 | Video Call | Discussed research proposal | Focus on getting the research proposal done for the subject |
| 17/5/2023 | Video Call | Progress update | Finish research proposal |
| 16/08/2023 | Video Call | Timeline for the semester | Discussed what we wanted to get done and how we might go about this. |
| 23/08/2023 | Video Call | Progress update | Designed Scanning PCB. Researching machine learning |
| 30/08/2023 | Video Call | Progress update | PCB received and soldered. Began embedded programming |
| 6/09/2023 | Video Call | Progress update | Embedded programming mostly done. ADC readings needs calibration. |
| 13/09/2023 | Video Call | Progress update | Began training ML model. Designing 3D printed enclosure. |
| 20/09/2023 | Video Call | Progress update | ML model of HDPE, LDPE & PP with ~90% accuracy. Enclosure complete. |
| 27/09/2023 | In Person Meeting | Progress update, physically showing hardware | Need to add more plastics and improve reliability |

| | | | |
|---|---|---|---|
| 11/10/2023 | Video Call | Progress update | Adding more plastics to model. Programmed LCD for output. |
| 18/10/2023 | Video Call | Progress update | Model now has 7 plastics and theoretical accuracy of 99%. |
| 25/10/203 | Video Call | Final meeting | Final testing with hardware. Start preparing for Engineering showcase. |

## A.2 BOM Tables

**8-LED**

*COTS Cost*

| Component | Name | Price (Qty 1) | Price (QTY 100) | Price (QTY 1000) |
|---|---|---|---|---|
| Photodiode | SD0050-3111-011 | $18.89 | $7.33 | $6.07 |
| OP Amp | OPA2376 | $4.66 | $3.21 | $2.18 |
| ADC | NAU7802SGI | $2.65 | $2.02 | $1.37 |
| LED Driver | TLC59108IPWR | $4.56 | $2.53 | $1.72 |
| LED 1 | 850nm | $1.60 | $0.76 | $0.57 |
| LED 2 | 940nm | $0.71 | $0.32 | $0.19 |
| LED 3 | 1050nm | $27.64 | $18.52 | $16.07 |
| LED 4 | 1200nm | $18.81 | $11.58 | $9.59 |
| LED 5 | 1300nm | $18.81 | $11.58 | $9.59 |
| LED 6 | 1460nm | $18.81 | $11.58 | $9.59 |
| LED 7 | 1550nm | $18.81 | $11.58 | $9.59 |
| LED 8 | 1650nm | $31.24 | $20.93 | $19.22 |
| Regulator | LP5951MFX-1.5 | $1.49 | $1.00 | $0.63 |
| LCD | 1.28" Waveshare | $31.36 | $16.02 | $11.54 |
| Microcontroller | ESP32 - WeMos | $9.60 | $9.41 | $8.83 |
| Connector | USB C | $0.24 | $0.24 | $0.20 |
| Battery | 800mAh 3.7V Lipo | $1.60 | $1.50 | $1.45 |
| Power Switch | SPDT Switch | $2.50 | $2.25 | $2.00 |
| Push Button | Tactile Button | $0.40 | $0.32 | $0.16 |
| 3D Print | - | $0.95 | $0.95 | $0.95 |
| Vibration Motor | PE Actuator | $1.95 | $1.95 | $1.95 |
| | | **$211.48** | **$130.11** | **$108.40** |

| | PCB Manufacture Price | PCB Assembly Price | Shipping Price | Total | Per Piece |
|---|---|---|---|---|---|
| Qty 5 | $3.17 | 12.7 | $2.28 | $18.15 | $3.63 |
| Qty 100 | $18.57 | 57.13 | $29.63 | $105.33 | $1.05 |
| Qty 1000 | $174.41 | 206.95 | $137.96 | $519.32 | $0.52 |

| | Total Price | Price Per Device |
|---|---|---|
| Qty 5 | $1,104.55 | $220.91 |
| Qty 100 | $13,564.33 | $135.64 |
| Qty 1000 | $112,669.32 | $112.67 |

**3-LED**

*COTS Cost*

| Component | Name | Price (Qty 1) | Price (QTY 100) | Price (QTY 1000) |
|---|---|---|---|---|
| Photodiode | SD0050-3111-011 | $18.89 | $7.33 | $6.07 |
| OP Amp | OPA2376 | $4.66 | $3.21 | $2.18 |
| ADC | NAU7802SGI | $2.65 | $2.02 | $1.37 |
| LED Driver | TLC59108IPWR | $4.56 | $2.53 | $1.72 |
| LED 1 | 850nm | $1.60 | $0.76 | $0.57 |
| LED 2 | 940nm | $0.71 | $0.32 | $0.19 |
| LED 3 | 1200nm | $18.81 | $11.58 | $9.59 |
| Regulator | LP5951MFX-1.5 | $1.49 | $1.00 | $0.63 |
| Microcontroller | ESP32 - WeMos | $9.60 | $9.41 | $8.83 |
| Connector | USB C | $0.24 | $0.24 | $0.20 |
| Battery | 800mAh 3.7V Lipo | $1.60 | $1.50 | $1.45 |
| Power Switch | SPDT Switch | $2.50 | $2.25 | $2.00 |
| Push Button | Tactile Button | $0.40 | $0.32 | $0.16 |
| 3D Print | - | $0.95 | $0.95 | $0.95 |
| | | **$68.66** | **$43.42** | **$35.91** |

| | PCB Manufacture Price | PCB Assembly Price | Shipping Price | Total | Per Piece |
|---|---|---|---|---|---|
| Qty 5 | $3.17 | 12.7 | $2.28 | $18.15 | $3.63 |
| Qty 100 | $18.57 | 57.13 | $29.63 | $105.33 | $1.05 |
| Qty 1000 | $174.41 | 206.95 | $137.96 | $519.32 | $0.52 |

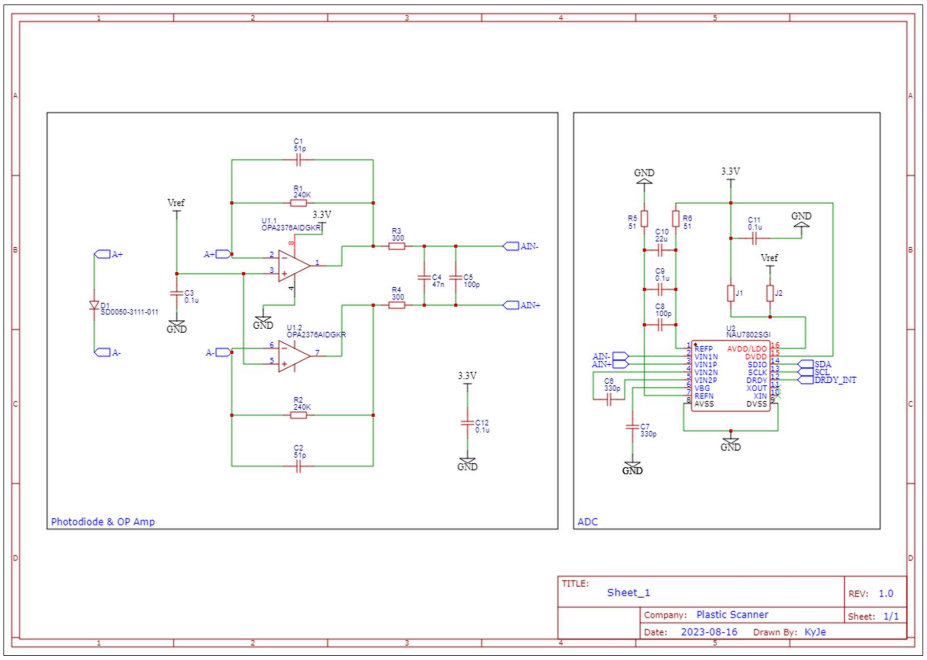
| | Total Price | Price Per Device |
|---|---|---|
| Qty 5 | $361.45 | $72.29 |
| Qty 100 | $4,447.33 | $44.47 |
| Qty 1000 | $36,429.32 | $36.43 |

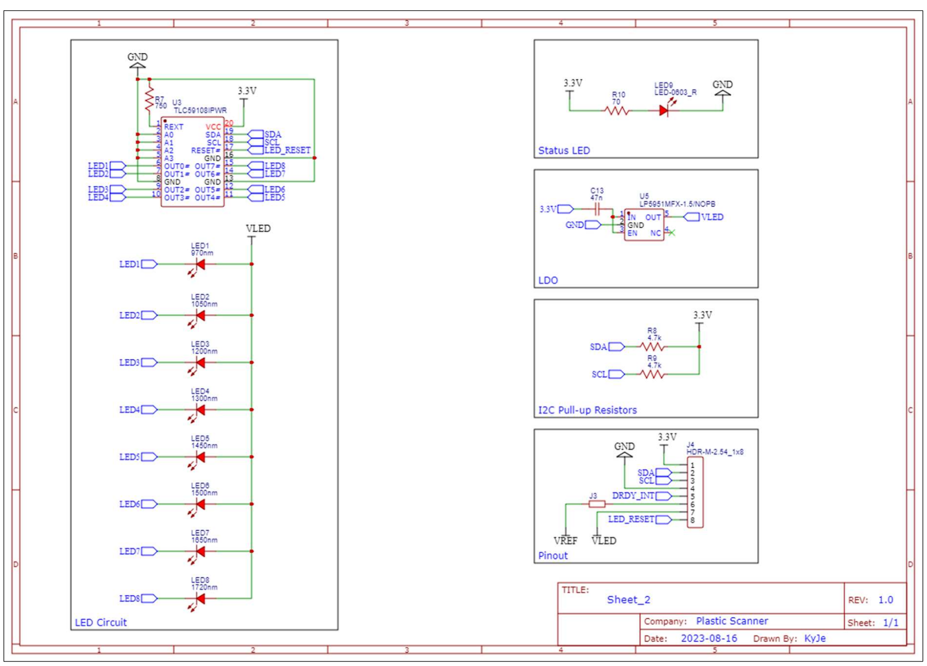
## A.3 Gantt Chart

**A Low Cost, Portable Plastic Identification Device**

| Stage Description | Duration | Start | End |
|---|---|---|---|
| **1. Concept Formulation** | **16** | **6 Mar 23** | **22 Mar 23** |
| a. Background research | 11 | 6 Mar 23 | 17 Mar 23 |
| b. Discuss possibilities with academic supervisors | 13 | 20 Mar 23 | 2 Apr 23 |
| c. Decision on scope and and literature review | 26 | 27 Mar 23 | 22 Apr 23 |
| **2. Explore Electronic & Machine Learning Requirements** | **27** | **3 Apr 23** | **30 Apr 23** |
| a. Experiment with off the shelf spectroscopic sensor | 6 | 3 Apr 23 | 9 Apr 23 |
| b. Research existing solutions and similar projects | 13 | 3 Apr 23 | 16 Apr 23 |
| c. Explore the machine learning approaches for classifying plastic types | 13 | 17 Apr 23 | 30 Apr 23 |
| **3. Design & Develop Sensing PCB** | **82** | **1 May 23** | **22 Jul 23** |
| a. Design & develop the PCB using accessible electronic components | 48 | 1 May 23 | 18 Jun 23 |
| b. Program & test the PCB | 17 | 19 Jun 23 | 6 Jul 23 |
| c. Iterate and continue to new prototypes as needed | 15 | 7 Jul 23 | 22 Jul 23 |
| **4. Develop Suitable Machine Learning Model** | **49** | **23 Jul 23** | **10 Sep 23** |
| a. Build a labelled dataset of plastic scans | 13 | 23 Jul 23 | 5 Aug 23 |
| b. Begin training a machine learning model on this data set | 7 | 6 Aug 23 | 13 Aug 23 |
| c. Continue to refine the model and the dataset to improve accuracy | 10 | 14 Aug 23 | 24 Aug 23 |
| d. Iterate and continue to new prototypes as needed | 16 | 25 Aug 23 | 10 Sep 23 |
| **5. Design & Develop Components for Handheld Device** | **48** | **21 Aug 23** | **8 Oct 23** |
| a. Select necessary components for a handheld device | 12 | 21 Aug 23 | 2 Sep 23 |
| b. Wire together and test the components | 7 | 3 Sep 23 | 10 Sep 23 |
| c. Design the device enclosure in CAD, accounting for all components | 11 | 6 Sep 23 | 17 Sep 23 |
| d. 3D print the enclosure | 6 | 18 Sep 23 | 24 Sep 23 |
| e. Iterate and continue to new prototypes as needed | 13 | 25 Sep 23 | 8 Oct 23 |
| **6. Integrate** | **10** | **9 Oct 23** | **19 Oct 23** |
| a. Assembly the mechanical and electronic components together | 10 | 9 Oct 23 | 19 Oct 23 |
| **7. Final Testing & Refining of Solution** | **10** | **20 Oct 23** | **30 Oct 23** |
| a. Develop a new Machine Learning Model with the new integrated device | 6 | 20 Oct 23 | 26 Oct 23 |
| b. Complete final testing of the device and model | 3 | 27 Oct 23 | 30 Oct 23 |

## A.4 PCB Schematics & Design



## A.5 GitHub Links

The following link it to a personal repository on my GitHub. This code will be cleaned up for external use and also submitted to the Plastic Scanner project: https://github.com/KyleJewiss/plastic-scanner/tree/master

The Plastic Scanner project GitHub can be found through the following link:
https://github.com/Plastic-Scanner

## A.7 Embedded Programming Flowchart