Final Report

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October 2023

Abstract & Plagiarism Declaration

To address the issue of electronic waste and cluttered workspaces in the Level 1 Labs, this project aims to develop an automated system for identifying and sorting electronic components. Utilising computer vision techniques, the system will classify electrical components such as resistors, capacitors, ICs, and MOSFETs, and sort them into designated bins. The project has been divided into three stages: initial development of a computer vision system for component identification, integration of a semi-automated sorting mechanism and finally, full automation of the sorting process. Supervised by Dr. Edward Stott, this project aims to solve the problems faced by the Level 1 Labs.

I affirm that I have provided explicit references for all the material in my Final Report that is not authored by me but is represented as my work. I have used GPTv4, as an aid in the preparation of my report. It was used for LaTeX formatting and spellchecking, however all technical content is original.

Contents

1 Project Specification

The motivation for this project is three-fold; to solve the problem of electronic waste and cluttered workspaces in the Level 1 Electrical Engineering Labs; to alleviate the time-consuming process of sorting electronic components from the Labs' technicians; and to bring the Lab closer to meeting the requirements for the LEAF (Laboratory Efficiency Assessment Framework) certification[25] that the Lab is currently working towards.

The LEAF certification is a framework that aims to improve the efficiency of laboratories by reducing waste, energy consumption, and costs. This project aligns with the LEAF certification's goals by reducing the amount of electronic waste produced by the Lab.

The project aims to achieve these goals by employing state-of-the-art computer vision techniques to classify various electronic components, and then sort them into designated bins. The project's deliverables are as follows:

- A computer vision system for component identification;
- An interface from which to observe and control the system's state;
- A sorting mechanism to properly place the components into designated bins.

After an initial consultation with Supervisor Dr. Stott and visiting the Level 1 Electrical Engineering Labs to discuss the project, samples

of the different electrical components commonly used were received, as follows:

- Resistors
- Capacitors
- Ceramic Capacitors
- Inductors
- Diodes
- MOSFETs
- Transistors
- LEDs
- Wires
- Integrated Circuits

2 Background

For the background of this project, it is necessary to consider literature related to the following:

- Existing computer vision systems for component identification
- Real-time computer vision architectures
- Mechanical design of existing sorting machines

Research into these topics will inform the decisions made in the design of the project and its various systems.

2.1 Existing Computer Vision Systems

A range of computer vision systems have been explored in the literature, ranging from PCA (Principle Component Analysis) Dhenge et al.[6] to more modern computer vision techniques like CNNs as used by Chand and Lal[3], Xu et al.[41]. However, given the rate of advancement of computer vision techniques, the techniques used in the literature reflect the state of the art at the time of writing, and so are not necessarily the most viable current techniques for the project, but they inspire novel approaches to the problem of component identification.

PCA with ANN (Artificial Neural Networks) as used by Dhenge et al.[6] is a relatively simple but outdated statistical technique that was successful in identifying nuts and bolts, which are very distinct components. In this paper, PCA is used as a feature extractor and then fed directly into, though not explicitly mentioned, a FCL (Fully Connected Layer), as the classifier. Although a valid approach, CNNs (Convolutional Neural Networks) are known to be much more effective at feature extraction, and do not "have the problem of low recall and accuracy", as mentioned by Xu et al.[41], that PCA may suffer from, so this approach is not viable for the project.

The authors Xu et al.[41] use the SqueezeNet CNN architecture to identify 22 different subcategories of electronic components, specifically resistors, capacitors, and inductors, achieving a TPR (True Positive Rate) of 99.999% with only a 2.67ms average inference time on a GTX 1050 2GB GPU (released in 2016) which is an impressive result. This work shows that a CNN is a viable approach to the problem of component identification, helping to inform the design of the project's computer vision system.

The paper by Muminovic and Sokic[21] discusses the use of an SVM (Support Vector Machine) to characterise resistors, by identifying the resistor's centroid (centre of mass), determining the resistor's orientation, and then analysing the bands to determine the resistor's value. This is directly applicable to the project, as it is a viable approach to identifying resistors, which are very distinct from other components, given the presence of colour bands. The paper's novel approach to identifying the resistor values allows it to achieve high accuracy (86%, however, the test images used are resistors that are positioned far away from the camera, as shown in Figure 5, and so the bands are very small, which will not be the case in the project's vision system, so the accuracy will likely be higher) which makes it a very promising resource for the project.

2.2 Computer Vision Architectures

For the problem of component identification, the computer vision system must be able to identify components in real-time, as the components may eventually be moving on a conveyor belt, captured using a camera facing down at the components. This means that the computer vision system must be able to identify components in a very short amount of time, and so the system must be computationally efficient. The envisioned system is designed to be self-contained, and as described in Section 3 (Implementation), the system will run on a Raspberry Pi 4, which has a 1.8GHz quad-core 64-bit ARM Cortex-A72 CPU and up to 8GB of RAM[8], and must also be accurate and able to control the other systems in the project in real-time.

This requires the Computer Vision system to be both computationally efficient and accurate, which is a difficult balance to strike.

For the explicit purpose of identifying electronic components, the paper by Chand and Lal[3] compares a range of different object detection architectures, including YOLOv3, YOLOv4 and

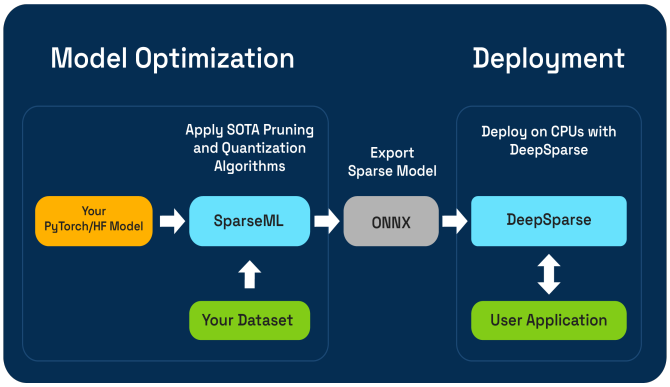

Figure 1: SparseML Pipeline[20]

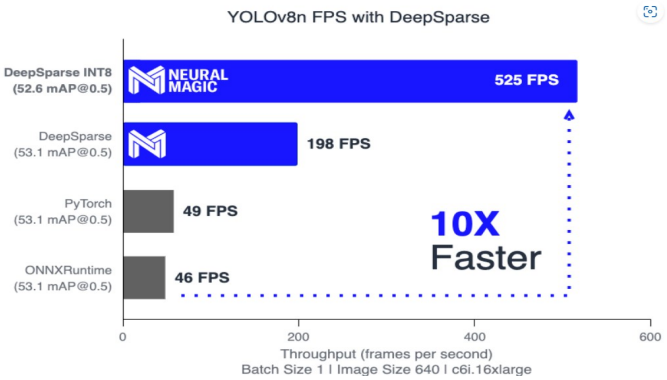

Figure 2: DeepSparse Performance[19]

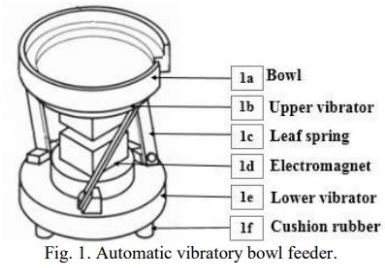

Figure 3: VBF[23]

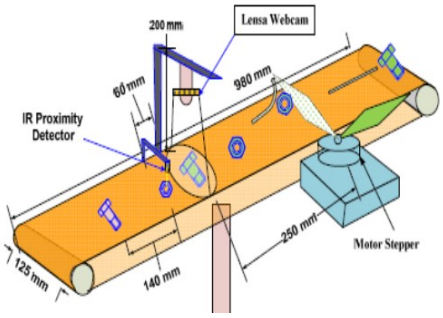

Figure 4: Conveyor Belt[6]

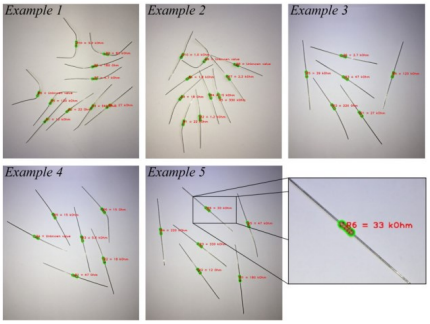

Figure 5: Resistor Test Set[21]

Faster SqueezeNet, with YOLOv4 achieving a mAP (mean Average Precision) of 98.6%.

YOLO (You Only Look Once) is a real-time object detection architecture, that is used very commonly in computer vision applications and is very effective at identifying objects in real-time Terven and Cordova-Esparza[38]. It makes use of a single CNN that takes in an image and outputs a list of bounding boxes and class probabilities for each bounding box. This is in contrast to other object detection architectures, such as R-CNN, which uses a CNN to propose regions of interest and then uses a second CNN to classify the regions of interest.

Other papers like Guo et al.[13] also comment on YOLOv4's effectiveness at identifying electronic components, achieving 93.94% mAP on a dataset of 20 different components, and the paper also comments on YOLOv4's ability to run in real-time, achieving 67 FPS, albeit on a powerful NVIDIA TITAN Xp GPU. For the Raspberry Pi 3B, the paper by Sismananda et al.[37] has shown to run YOLOv3 at a very low 1 FPS, with an IoU (Intersection over Union) accuracy of 86.7%, which is relatively low.

However, efforts made by Neural Magic[19] in the optimisation of YOLOv5 and YOLOv8 show performance improvements of up to 10x on CPUs, through their open-source optimisation toolkit SparseML[20] and CPU inferencing runtime, DeepSparse[18]; a very promising result.

2.3 Training Methods

When training a neural network, it is important to have training data. For a computer vision system, this means having a dataset of images that are representative of the conditions that the system will be used in and are well-labeled with bounding boxes and class labels. It is important to have a large dataset to ensure that the model is robust and generalises well, which is time-consuming to create.

To solve this problem, a paper by Yang et al.[42] proposes many different training techniques, the most promising of which is semi-supervised learning. In this approach, the model is trained on a small labeled dataset, and then used to label a large unlabelled dataset, which is reviewed and corrected by a human.

This process is repeated until the model is sufficiently accurate, and then the model is trained on the large labeled dataset. This approach is very promising, as it allows for the training of a robust model with a large dataset, without the time-consuming process of manually labeling the entire dataset.

2.4 Mechanical Design

Transport Mechanisms

The paper by Dhenge et al.[6] depicts a conveyor belt system that transports nuts and bolts to a computer vision system for identification, which aligns with the goals of the project. The hardware prototype is shown in Figure 4, and a down-facing webcam is used to capture images of the components as they pass by. The webcam uses Principle Component Analysis (PCA) to identify the components, which will be discussed in the next section.

The components then separate into two chutes, one for nuts and one for bolts, using a stepper motor, which may be useful for the future design of the sorting system. Additionally, the approach taken by the paper Quilloy et al.[31] to sort Philippine table eggs also features a similar conveyor belt system, a down-facing camera and an arm to sort the eggs into different categories.

The approaches taken here are similar to industrial sorting systems seen in videos while researching for this project; this approach seems to answer three major design questions for the project; how to transport the components to the computer vision system; how to transport the components from the computer vision System to the sorting system; and the placement of the camera.

Other approaches include vibratory feeders[17], which use precise vibrations to orientate and transport components, and pneumatic systems from Abe et al.[1] (also suggested by project Supervisor Dr. Stott when dicussing transporting mechanisms in project meetings), use air pressure in tubes to transport components. These approaches require more complex hardware, and lack the easily achievable precision of the conveyor belt system, for example in the case of the pneumatic system, a complex network of tubes and valves and an air compressor is required, which is not practical for the project. Robotic arms are commonly used in the industry for sorting, however, this is not viable as this would either require an expensive robotic arm, or a complex system of motors and actuators to move the components.

From the approaches above, it seems that a conveyor belt with a down-facing camera is the most viable approach to transporting the components. Initially, the aim was for the system to be semi-autonomous, with a design allowing the camera to face upwards. This configuration would enable the user to place the component on an acrylic plate directly above the camera for immediate identification, enabling easy user interaction as the view of the component is not obstructed. Having the camera face-down would block the user's view of the component, which would be an inconvenience, and as such, the current design of the system features an up-facing camera. However, this will be changed to reflect the research outlined above, in the next stage of the project.

Bowl Feeders

While researching for this project, and especially in videos[40], it seems most industrial sorting machines use a Vibratory Bowl Feeder (VBF) to help feed components into the sorting system; as shown in Figure 3, the VBF consists of a bowl that vibrates coupled with a spring and electromagnet. The paper by Nam et al.[23] explores the optimal design of a VBF for USB keycaps, by attempting to identify the ideal parameters for the structure of the bowl, sorting track, mounting adapter, and suspension system. The paper also uses modal analysis to determine the natural frequencies of the system and uses this to avoid resonant conditions that might cause inefficient or erratic operation.

This paper is useful as it provides a comprehensive overview of the design of a VBF, and provides a good starting point for the design of the VBF. In the future, the project may make use of one for fully autonomous sorting. The paper also provides a good overview of the design considerations for the VBF, and so can be used as a reference during the design process.

Additionally, Reinhart and Loy[34] delve into a mathematical model of a VBF, optimising more on the overall performance of the VBF rather than efficiency, and Silversides et al.[36] provides a good overview of the forces involved in the operation of a VBF, strengthening the basis for its design and viability.

The paper by Zhengyang Zhang[43] outlines a sorting system for vials and does not make use of a VBF, instead opting for a turntable design that mechanically orientates the vials. It primarily operates by using a design that is specific to the geometry of the vials, and so does not apply to this project, however, it does provide a good insight into the design of a sorting system.

An alternative to the VBF could be a robotic

arm; fine control over movement would be necessary as the components are small and may be tangled, however, as mentioned before would require its own set of sensors and camera systems. As the components can be tangled, there are not many viable alternatives to the VBF or a robotic arm, so between these two solutions, it seems that the VBF is the most viable approach if the system is to be fully autonomous, as the vibrations of the VBF would help to untangle the components.

2.5 Key Takeaways

After reviewing the literature, the following key takeaways were made:

The most viable approach to the problem of component identification is to use a CNN, specifically the YOLOv8 architecture, as they are very effective at classification tasks, which translates to being able to identify electronic components. With the ability to optimise the model using SparseML and DeepSparse, the model may be able to run on the Raspberry Pi 4 in real-time, which is a key requirement of the project. Additionally, the YOLO architecture may be covered in the modules Deep Learning COMP70010 and Machine Learning COMP70014, enriching the understanding of this architecture.

The most viable approach to the problem of component transportation seems to be a conveyor belt system with a down-facing camera, and so the design of the computer vision system will be based on the research outlined above in the next stage of the project.

A VBF is the most viable approach to the feeding mechanism of the sorting system, and so the design of the VBF (if employed in the project) will be based on the research outlined above.

Additionally, the YOLOv8 architecture will be employed, making use of the SparseML and DeepSparse optimisation tools with semi-supervised learning to train the model.

3 Implementation

Three systems compromise the project:

- The Hardware, Mechanics and Electronics
- The software that coordinates the various components
- The computer vision system

It is important to note that the system has undergone significant design changes during its development. The following section will discuss the final implementation of the system, and a seperate section has been dedicated for discussion on design changes and problems faced during development that helped inform the final design.

3.1 Hardware, Mechanics & Electronics

The hardware, mechanics and electronics (HME) of the system are the physical components that make up the system. It is necessary to first consider the HME of the system as they are the foundation upon which the rest of the system is built upon; for example, when designing the computer vision system, it should utilise training data that was collected using the HME that the system will be deployed on, ensuring that the system is robust to the conditions it will be used in.

To keep track of the HME, a spreadsheet was created that contains all the components of the system (otherwise known as the Bill of Materials or BOM), as well as the cost of each component. A sample of this spreadsheet can be found in Appendix Figure 22.

3.1.1 Hardware

The following hardware components have been used in the system:

- Raspberry Pi 4 Model B 2GB[8]
- 7" Touchscreen Display[5]
- 24V dc, 6.25A, 150W Power Supply
- Okdo Adjustable Focus OV5647 Camera[26]
- LED Light Ring
- NEMA17 42-40 Stepper Motor + DRV8825 Driver

Raspberry Pi 4 Model B 2GB

The Raspberry Pi 4 Model B was chosen as the main component of the system and is the central hub that all other components are connected to. This model was chosen as it is regarded as a reliable SoC (System on Chip), is widely used in the industry and was used in the module ELEC96018 Embedded Systems. It has a large amount of software and driver support, ensuring confidence in finding solutions to any potential issues that may arise. Additionally, it has GPIO pins that can be used to control other components. It also has a dedicated CSI camera port which allows for a camera to be connected directly to the

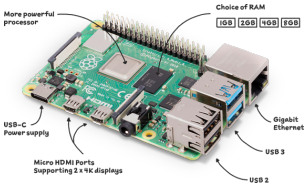

Figure 6: Raspberry Pi 4 Model B 2GB[8]

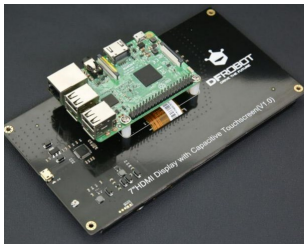

Figure 7: DFRobot 7" Touchscreen Display[5]

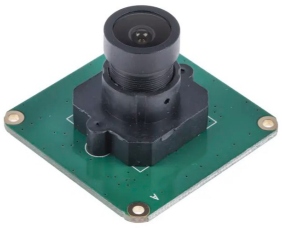

Figure 8: Okdo Adjustable Focus OV5647 Camera[26]

Figure 9: Power consumption of the system

SoC, which is necessary for the computer vision system.

It also has WiFi support, allowing for SSH and remote development software, as well as an HDMI port for the display. Originally, the 4GB model was ordered however an issue with the EE Stores resulted in receiving the 2GB model instead. This was not an issue as the 2GB model was sufficient for the project. The decision to not return the 2GB model is because it was not possible to order a new Pi without returning the old one, halting the development of the system.

An alternative to the Pi family of SoCs are Arduinos, but while they are capable of controlling the components of the system, and potentially drive an LCD, the microcontrollers are typically not powerful enough to run the computer vision system and stream video from the camera, so they cannot be used as a replacement for the Pi.

A viable alternative to the Pi is a NVIDIA Jetson Nano[24], as it is designed for computer vision applications and has a dedicated GPU. The dedicated GPU would reduce the likelihood of the computer vision system being a bottleneck, and it has a CSI port for the camera; in terms of CPU performance, the Nano is weaker than the Pi, having a quad-core ARM Cortex-A57, whereas the Pi has a quad-core ARM Cortex-A72[8]. However, the worse CPU performance is offset by the dedicated GPU, and the Nano has 4GB of RAM, making the Nano a very attractive alternative to the Pi. The Nano's drawback is that it is significantly more expensive than the Pi (up to 3x from retailers), and given the ability to optimise the computer vision system as discussed in Section 2 (Background), the Pi is still a viable choice for the computer vision system.

To address the lack of a dedicated GPU for inference, an article from Medium[2] benchmarked the Pi's performance on various computer vision tasks with various accelerators like the Intel Neural Compute Stick 2 and the Google Coral USB Accelerator against other SoCs like the Jetson Nano and the Coral Dev Board. It was found that the Coral Dev Board was the best performing, however the Pi using optimisation libraries like TensorFlow Lite showed promising results, which helps to strengthen the argument for using the Pi for the computer vision system, especially with the SparseML and DeepSparse libraries that were discussed in Section 2 (Background).

The benchmarks can be found in Appendix Figure 24.

7" Touchscreen Display

The DFRobot 7" Touchscreen Display was chosen as it is a relatively cost-effective display that is compatible with the Raspberry Pi. It has touchscreen support and has a Raspberry Pi 4 mount on its back, as well as HDMI adapter boards to connect to the Pi. This means that a physical mount for the Pi does not need to be designed, and only a mount for the display is required. The display is also powered by the Pi, so no additional power supply is required.

24V dc, 6.25A, 150W Power Supply

Two parameters were taken into consideration when choosing a power supply: the power output and the voltage.

- **Power Rating**
  The power supply must be able to drive all components in the system with overhead in case of spikes in power consumption. In this first stage, the system only consists of the Raspberry Pi, the display, LED lights and the camera, making for a power consumption of under 20W, recorded using a smart plug with a power meter as shown in Figure 9. However, in the future, the system will likely need to drive additional motors and sensors, so the total

power consumption will be higher. Even with accounting for this, the power consumption will be under 100W, so a 150W power supply will be sufficient, allowing a 50W overhead. In hindsight, this may be considered excessive.

- **Voltage Rating**
  The voltage of the power supply must be greater than or equal to the highest voltage of any component in the system; this is necessary as there are only step-down converters available on hand, so choosing a higher voltage allows the stepping down of the higher voltage to the required voltage for each component. 24V was chosen as it is a common voltage for stepper motors, which may be used in future stages of the project. It is also used for some LED strips, which are used in this stage. The Pi 4 uses 5V and the LED Ring uses 12V, which the 24V power supply can be stepped down to.

Okdo Adjustable Focus OV5647 Camera

For the Computer Vision system, a camera is required to capture images of the components. The Okdo Adjustable Focus OV5647 Camera was chosen as it is CSI compatible, meaning it can be connected directly to the Raspberry Pi, and has a manual focus ring, allowing it to be used as a macro camera to capture images of small components placed directly above it. The manual focus ring allows the camera to be specifically tuned to the design of the system, allowing for the best possible image quality. It also has a 5MP sensor[27], which is sufficient for the computer vision system, as high-resolution images would be preprocessed and reduced, only adding to the amount of processing required.

LED Light Ring

An LED Ring is required to illuminate the components so that the camera can capture images of them. Initially, a 12V LED Ring was chosen as it would allow for a uniform light source and could be mounted directly below the camera; however, for reasons explained in the next section, it was replaced with a 5V WS2812B LED strip as it solves the issues faced with the LED Ring.

3.1.2 Mechanics

To house the components, a 3D-printed housing was designed. It features a modular design, allowing for an iterative design process where different components of the system can be worked on independently. It also allows for easy replacement of components should the design prove to be inadequate. The housing was designed in FreeCAD[9], a free and open-source parametric CAD software.

The parametric design allows for easy modification of the design should changes need to be made - with good design practices, large systematic changes can be made by simply modifying a few numerical parameters. The design was then printed using a 3D printer, a heavily modified Voxelab Aquila C2.

All parts are printed in PLA (Polylactic Acid), a biodegradable thermoplastic that is commonly used in 3D printing[32]. The design at this stage does not require any special properties from the material, so PLA is sufficient. The biodegradable properties of PLA also align with the ethical considerations of the project, as discussed in Section **??** (Ethical, Legal, and Safety Plan).

For this stage of the project, three major components for the housing were designed:

PSU Housing

The PSU housing contains the power supply and ensures that all high-voltage components are safely enclosed. It also houses the power switch, the power socket and the terminals. As step-down converters are required for the Pi and LED Ring, the PSU housing also contains mounting points for the step-down converters, as well as a mounting plate to ensure that the step-down converters are mounted flat to the PSU housing.

Camera Housing

The camera housing contains the camera and the LED Ring. It also contains the mounting points for the camera and LED Ring. The camera housing will also mount an acrylic plate above the camera, so components can be placed on the plate and be imaged by the camera.

From bottom to top in Figure 11, are the bottom casing, LED Ring mount, camera mount, light diffuser, middle casing and top casing.

LCD Display Housing

The LCD housing contains the LCD and the Raspberry Pi. As the 7" DFRobot LCD has a Raspberry Pi 4 mount on its back, an explicit mount for the Pi is not required. The mount will position the LCD at an angle, so it can be viewed from above. The LCD simply slides into the mount, allowing for easy removal and also

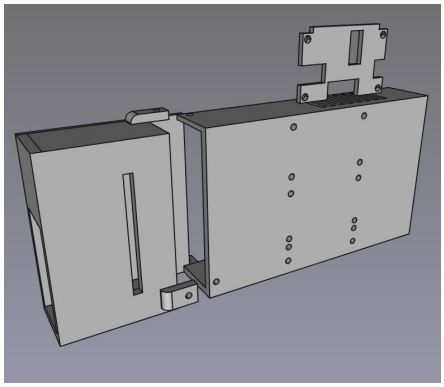

Figure 10: PSU Housing

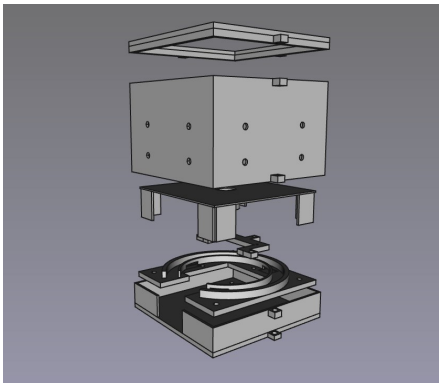

Figure 11: Camera Housing

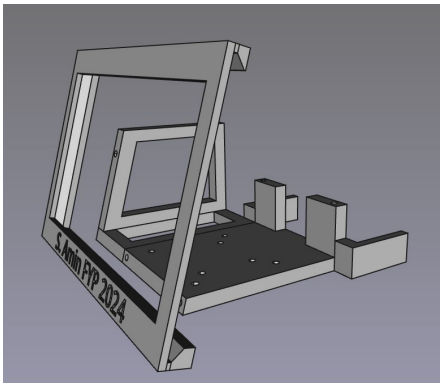

Figure 12: LCD Display Housing

contains mounting points to secure the LCD to the camera housing.
The LCD housing is split into two parts; the LCD cover, where the LCD slides into, and a base plate, which mounts to the camera housing. The LCD cover is then mounted onto the base plate, securing the LCD in place.

The components are secured using brass M3 heat-set inserts and M3 screws. The heat-set inserts are inserted into the 3D-printed parts using a soldering iron, and the components are then screwed into the inserts. This allows for easy removal of components should changes need to be made to the design, following the modular design principle.

The design of the system at this stage is shown in the Appendix in Figure 23.

3.1.3 Electronics

As the project is a physical system, several electronic components are required to make the system work.

Power Supply
As mentioned in Sections 3.1.1 and 3.1.2, the system is powered by a 24V, 6.25A, 150W power supply, and must be stepped down to 5V for the Pi and 12V for the LED Ring. This is achieved using an XL4015 Step Down Converter[16], a variable step-down converter that can output up to 75W. The high power rating of the step-down converter allows for a large overhead, which is useful for future stages of the project where additional components may be added to the system.

Raspberry Pi 4
To power the Raspberry Pi, a standard USB-A to USB-C cable was chosen and was connected to a female USB-A breakout board connected to the 5V step-down converter. This allows for easy removal of the Pi should changes be made to the system, and prevents the unnecessary cutting of cables.

As the Pi is mounted to the LCD, a USB-A to Micro USB cable is used to connect the Pi to the display, which is then connected to the Pi's HDMI port, using a supplied HDMI adapter board.

LED Lighting
As mentioned in Section 3.1.1, initially, a 12V LED Light Ring was used and was changed to a WS2812B 5V LED strip, for issues described later. To enable the ability to dim the LED Ring, a MOSFET was used to control the LED Ring. As shown in Figure 13, the LED Ring was connected to a 12V supply (achieved using the 12V step-down converter) and parallel to a 100μF capacitor, which is used to smooth out the voltage spikes.

The LED Ring was then connected to an N-channel MOSFET IRLZ44N[14], which is controlled by a PWM-enabled GPIO pin on the Pi. This GPIO pin is connected to a 1kΩ resistor, which prevents potential overcurrent from damaging the Pi. The MOSFET is then connected to ground, completing the circuit.

The IRFZ44N is a logic level MOSFET, meaning it can be fully turned on with a 3.3V gate voltage, which is the voltage of the Pi's GPIO pins, and the high switching speed (up to 1 mHz) of the MOSFET allows for the LED Ring to be PWM controlled, allowing for the brightness of the LED Ring to be controlled.

3.2 Software

The entire system is controlled by a Raspberry Pi 4B running a very lightweight Linux distribution called DietPi[7]. The goal for the entire system is to be run locally on the Pi, so the Pi will be responsible for running the computer vision system, controlling the hardware, and running

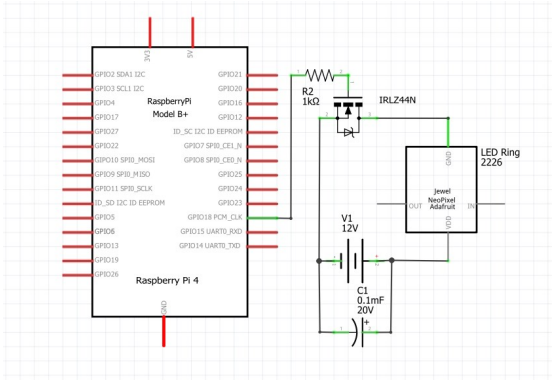

Figure 13: Wiring Schematic for MOSFET, made with Fritzing[10]

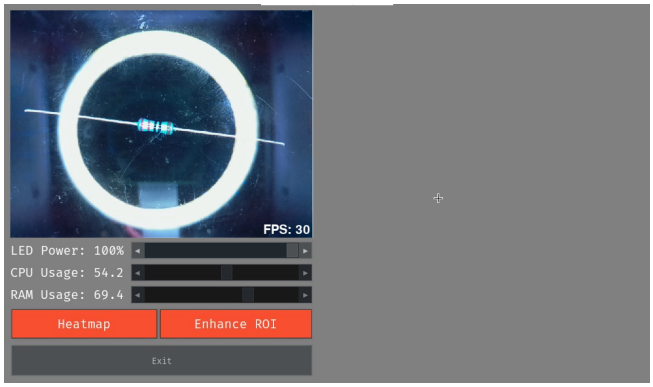

Figure 14: Main UI, captured using RealVNC[33]

the user interface. In order to achieve this, the following software components are required:

- The User Interface
- The Computer Vision system
- The Hardware Control system

The system's software is written in Python[30], which is well suited for the project given the availability of libraries for computer vision and hardware control. Again, the concept of modularity underpins the design of the software, and so each component is designed to be independent of the others and can be developed in parallel.

All written Python code adheres to a style defined in a .pylintrc file, which is a configuration file for the pylint[29] linter. This ensures that the code is consistent and readable. The code is also documented using docstrings for readability and maintainability. Each software component is designed to be self-contained so they can be run independently for testing purposes.

All software constants are defined in a constants.py file, which is imported by all other Python files, allowing for easy modification of constants that define the behaviour of the system which is useful for testing and debugging.

Additionally, a lot of thought went into streamlining the development process to ensure that the system is easy to develop and maintain. For example, Visual Studio Code's[4] Remote SSH extension is used to develop the system remotely, as it allows developing the system on a much more powerful laptop, while using the familiar VSCode environment with any extensions that help streamline the development process. This is crucial as the Pi is not very powerful, so compiling and running the system on the Pi may be slow and cumbersome.

The Pi uses Git[11] for version control, and the repository is hosted on GitHub[12], with a dedicated branch for the Pi that is regularly updated with the main branch. The vision system and the laptop also maintain their own Git branches which are regularly updated with the main branch, ensuring that all systems are running the same code. This is crucial as it enables development on a more powerful laptop, and then synchronises the changes to the Pi, without having to manually copy any files over.

During development, the Pi connects to the laptop's WiFi hotspot and is configured to be discoverable with the Pi's hostname, facilitating easy access to the Pi through SSH and a VNC Viewer without needing the Pi's IP address, which is dynamic. The Pi also makes use of SSH keys, allowing connection to the Pi without needing to enter a password every time, ensuring quick and easy access.

User Interface

As the system is intended to be self-contained, it is important to have a user interface that displays all relevant information to the user and allows them to interact with the system. The UI is displayed on the 7" touchscreen display, and is written using Pygame[28];

This design decision was made after experimentation with other UI libraries like Tkinter[39], however it was found that Pygame was the most viable for several reasons; it contains a module for camera streaming, which is used to display the camera feed on the UI, and can also be used to feed the camera frames to the Computer Vision system; there is a very large amount of control provided by Pygame over the UI, especially in terms of performance. This is crucial as the UI is only there to provide information to the user,

and so it must not interfere with the computer vision system or the hardware control system. With an additional library named pygame_gui[22], it is possible to create a UI with GUI elements like buttons, text boxes, and drop-down menus, making for a fully comprehensive UI library.

In Figure 14, the current version of the UI is shown. On the left, the camera feed and camera frame rate are displayed, with the system CPU and RAM usage displayed, for monitoring purposes. There is a slider to adjust the power of the connected LED Ring light, as well as two buttons related to the Computer Vision system.

The right side is empty for now but will be used to display information about the computer vision system and the hardware control system.

3.3 Computer Vision

The computer vision system should be trained on data that is representative of the conditions it will be used in, and because of the previously mentioned issues with the mechanical design of the system, the computer vision system was not developed at this stage. The data collection process is manual and time-consuming, so it is far more efficient to ensure that the mechanical design is finalised and that the foundation of the project is robust and reliable. As will be discussed in Section **??** (Project Plan), the mechanical design will be overhauled in the next stage, so if data was collected for the computer vision system in this stage, it may have been rendered useless in the next stage.

However, this does not mean that no work was done on the computer vision system. As per Section 2 Background, it was determined that YOLOv8 is the most suitable model for the computer vision system. As such, several tools were developed to aid in the development of the computer vision system.

Additionally, careful consideration of the Computer Vision system pipeline was done in this stage.

3.3.1 Data Collection

For the task of component identification, the computer vision system must be trained on data that is representative of the conditions it will be used in. As such, the data collection process is manual and time-consuming. For this reason, a customtkinter[35] script was developed to aid in the data collection process. The script allows easy labelling of images with bounding boxes and class labels; and will save the labels in a format that is compatible with the YOLOv8 model. The script also streamlines the labelling process using shortcut keys, and sorts each image into a folder based on the class label, making it easy to manage the data. Given that this is a custom script, features can be easily added or removed - it is likely that features such as component orientation will be added, so a custom script is very useful.

This script works in conjunction with the UI, seen in Figure 14, running on the Raspberry Pi (made possible using RealVNC[33], a remote desktop application), allowing for very easy labelling of images with bounding boxes and class labels.

The script has support for multiple components, including:

- Resistors
- Capacitors
- Ceramic Capacitors
- Inductors
- Diodes
- MOSFETs
- Transistors
- LEDs
- Wires
- Integrated Circuits

A screenshot of the script at work can be seen in Figure **??**.

A Jupyter Notebook[15] was also developed to aid in developing the computer vision system. This is common practice as it allows code to be run and the data associated with it to be inspected, which is very helpful for debugging purposes. It has the capability of training every model that will be used in the computer vision system and contains features like data augmentation, checkpointing, and model evaluation.

The data augmentation feature is very useful as it retains the original data, should more labels need to be added or modified in any way. The checkpointing feature allows facilitates saving the model at any point during training, which serves as a backup but also allows training to resume from specific points. This is useful as it helps to protect against overfitting. The model evaluation feature allows for the evaluation of the model on a test set and provides useful metrics like precision, recall, and mAP (mean average precision). This is useful for evaluating the model's performance, and also for comparing the performance of different models.

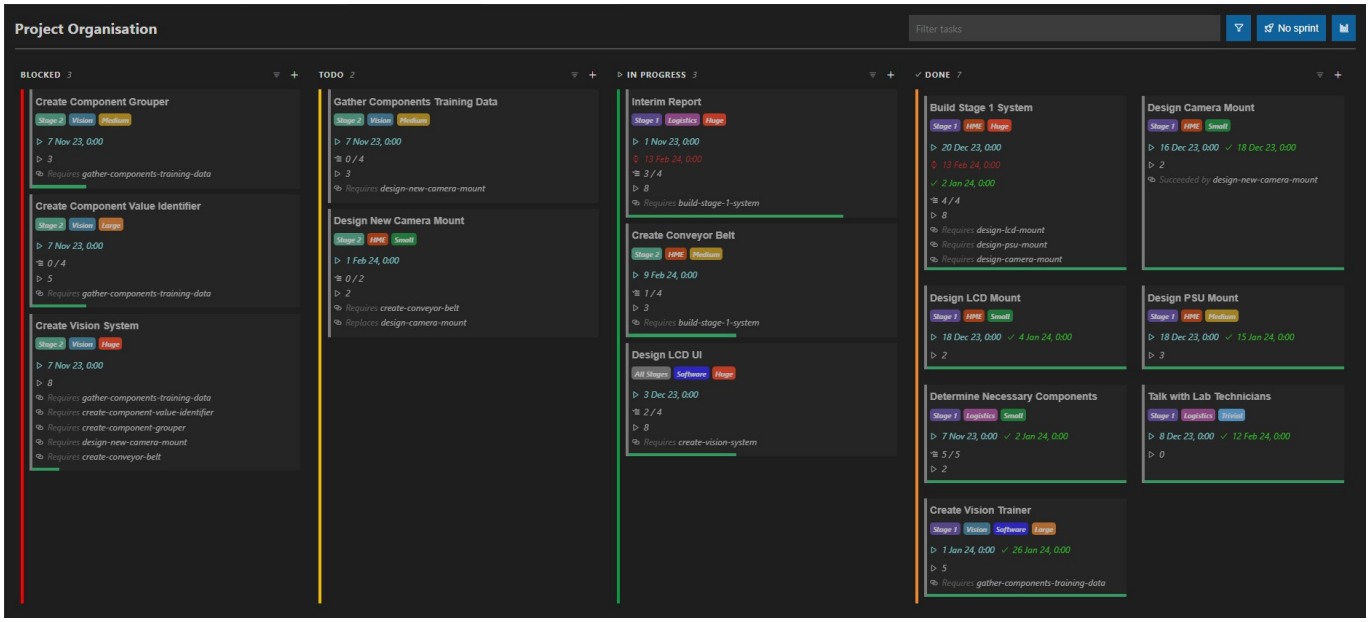

Figure 15: Project Plan

3.3.2 Vision System Pipeline

The computer vision system pipeline is the sequence of steps that the computer vision system takes to identify components.

The system pipeline is as follows:

- **Preprocessing**
  The image is preprocessed to improve the quality of the image and to make it easier for the model to identify components, ensuring uniformity and consistency in the data.
- **Component Detection**
  The image is fed to the model, which outputs a class, confidence score, bounding box, and orientation for each component.
- **Component Value Identification**
  The value of the component is identified from the sub-image within the bounding box and is used to further classify the component.

While a single model can be used to identify components, it is necessary to use two models to identify the value of the component. This is because the value of the component may differ depending on the type of component. For example, the value of a resistor is read from the colour bands, whereas the value of a capacitor is read from the text printed on the component. As such, each component may require a different model to identify its value.

This is not an issue as it conforms to the modular design of the system, and allows for easy extensibility. For example, if a new component is added to the system, it is easy to add a new, or reuse, an existing model to identify the value of the component; however the component detection model will need to be retrained as the dimensionality of the output layer will change due to the addition of a new class. The Jupyter Notebook developed for the Computer Vision system makes this process very trivial, as it would simply require adding the new component to the list of components, and the Jupyter Notebook will handle the rest.

4 Problems and Changes

3D printing is typically an iterative process, where the design is printed, tested, and then modified based on the results. This further reinforces the need for a modular and parametric design, as it allows for easy modification of each component. After a few iterations with errors due to tolerances and slightly incorrect measurements, (not relevant to the technical content of this report) a design was produced that physically fit together and mounted the components as intended, however when combined with the software and electronics, a few problems were encountered that were overcome by making some design decisions that were discussed with the project's supervisor, Dr. Stott.

4.1 Mechanical Design Problems

The first design problem was the initial design of the LCD mount. As mentioned in Section 3.1.2,

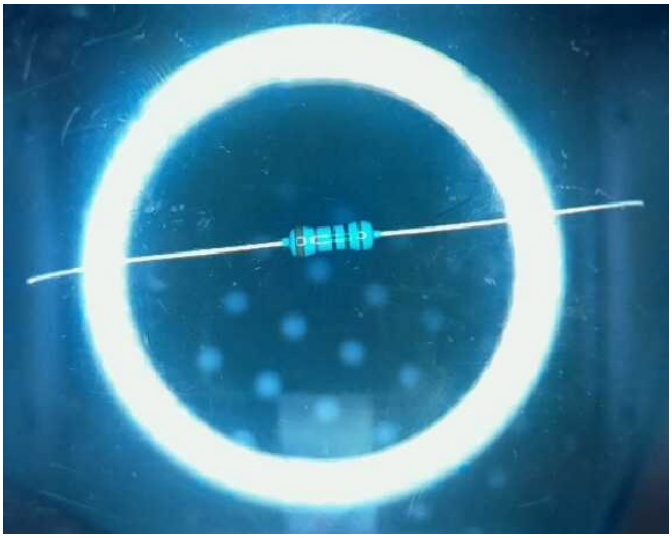

Figure 16: Glare from LED Ring

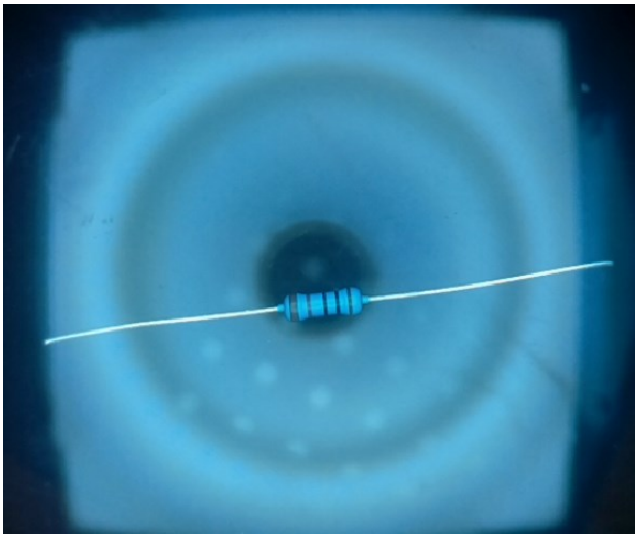

Figure 17: Diffused Light

the LCD housing is split into two parts; the LCD cover, where the LCD slides into, and a base plate, which mounts to the camera housing. The initial design of the LCD cover was only mounted to the base plate using two M3 screws at the base as shown in Figure 18, which made it unstable and prone to wobbling. Over time, this would put stress on the plastic, causing it to break. To solve this, a third mounting point was added to the LCD cover in the form of a brace that reaches halfway up the LCD cover, as shown in Figure 19, increasing the stability of the LCD, and preventing it from wobbling.

The second design problem was the design of the camera housing. As mentioned in Section 3.1.2, the camera housing contains the camera and the LED strip. The camera itself is not a macro lens, but rather a standard lens with an adjustable focus. The workaround is to set the focus as close as possible, and then determine the optimal distance between the camera and the object to be imaged. This is done by placing an object on the acrylic plate. Initially, the height of the camera housing was too short as shown in Figure 20, resulting in a blurry image, which was remedied by simply changing the parametric parameters that define the height of the camera housing, as shown in Figure 21.

The above design problems were solved by simply modifying the design, however, the third design problem was more complex. As mentioned in Section 3.1.2, the approach to imaging components is to place them on the acrylic plate, and then image them using the camera. However, when doing so, the light from the LED Ring would reflect off the acrylic plate as shown by Figure 16, resulting in an incredible glare that would obscure the image of the component. There was an attempt to 3D print a light diffuser to reduce the glare Figure 17, however, this was not effective and instead caused the entire image to be affected by the reflection of the LED Ring. This was a major design problem as, in the non-diffused image, any components in the glare of the ring were obscured, and in the diffused image, the entire image had incorrect colours and was partially obscured. To solve this, three solutions were considered:

- **Polarising Filter**
  Polarising filters can be used to reduce glare by filtering out light that is polarised in a certain direction.
- **Different Light Source**
  The LED Ring was chosen as it provides a uniform light source as it would surround the camera, however, it is possible to use a different light source that does not cause glare, for example, an LED strip that is mounted above the camera near the acrylic plate.
- **Down-facing Camera**
  Instead of imaging the components from below, the camera can be mounted such that it is facing down, and images the components from above, as explored in Section 2 (Background). The issue is that the light of the LED Ring bounces off the bottom layer of the acrylic plate, so any components on top are obscured.

However, in the end, none of these could be considered because of the electronics design problem discussed in the following section.

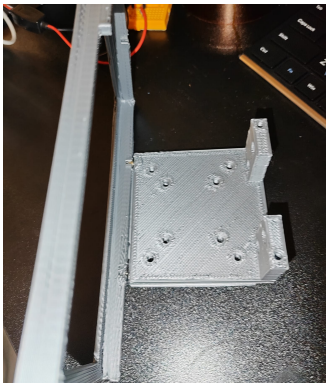

Figure 18: Unbraced Screen

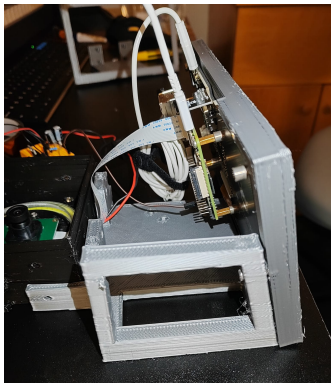

Figure 19: Braced Screen

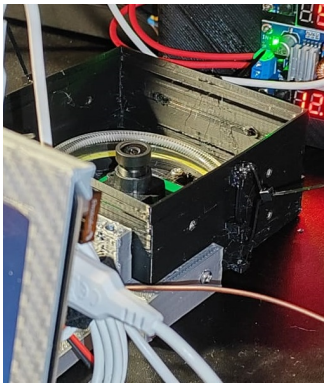

Figure 20: Short Camera Housing

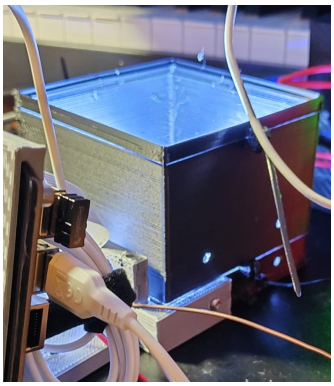

Figure 21: Optimal Camera Housing

4.2 Electronics Design Problems

Attempting to dim the LED Ring resulted in very sporadic flickering, and it did not react with changes to the frequency of the PWM signal despite the MOSFET control circuit shown in Figure 13. Originally, it was thought that the issue was due to the MOSFET, as initially a MOSFET with a higher gate threshold voltage (IRF520N) was used, and so it was replaced with one with a lower gate threshold voltage. However, this did not solve the issue, and a capacitor was added in parallel to the LED Ring to buffer the voltage, but to no avail. The LED Ring seemed to be a simple component with no additional circuitry except for the LEDs, so it was not clear why it was not dimmable. Supervisor Dr. Stott was also unsure as to why it was not dimmable and proposed a different circuit with an inductor and diode but this requires a much higher switching frequency than the Pi's PWM signal can provide, and so it was not viable.

For these reasons, and after reviewing the literature as discussed in Section 2, it was decided that the camera mount was to be redesigned to be down-facing (as a conveyor belt will also be used in the future) and to replace the LED Ring with a WS2812B LED strip, as these are designed to be dimmable. They are also addressable, however, this is not a feature that is required at this stage of the project.

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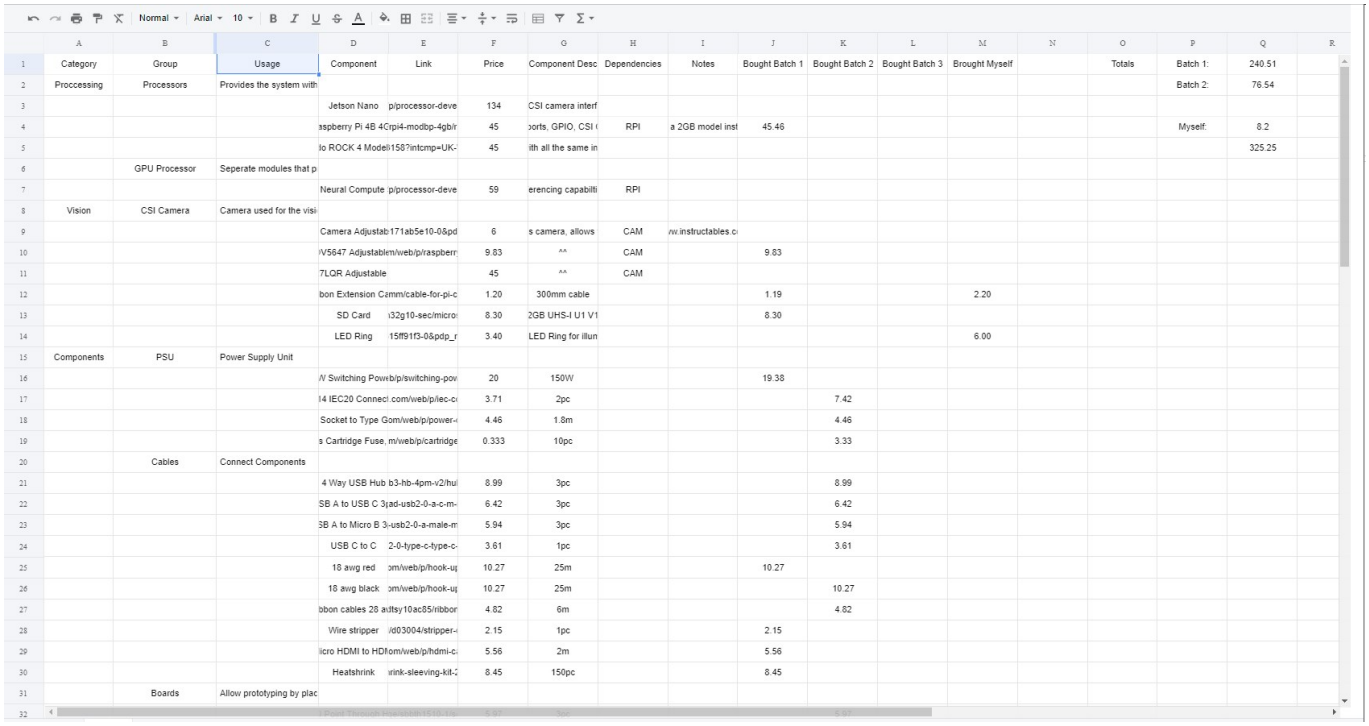
6 Appendix

Bill of Materials



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17				14 IEC20 Connec	l.com/web/p/iec-c	3.71	2pc				7.42							
18				Socket to Type G	om/web/p/power-	4.46	1.8m				4.46							
19				s Cartridge Fuse	m/web/p/cartridge	0.333	10pc				3.33							
20		Cables	Connect Components															
21				4 Way USB Hub	b3-hb-4pm-v2/hu	8.99	3pc				8.99							
22				SB A to USB C 3	ad-usb2-0-a-c-m-	6.42	3pc				6.42							
23				SB A to Micro B 3	usb2-0-a-male-m	5.94	3pc				5.94							
24				USB C to C	2-0-type-c-type-c-	3.61	1pc				3.61							
25				18 awg red	om/web/p/hook-up	10.27	25m			10.27								
26				18 awg black	om/web/p/hook-up	10.27	25m				10.27							
27				bbon cables 28 a	ultsy10ac85/ribbon	4.82	6m				4.82							
28				Wire stripper	/d03004/stripper-	2.15	1pc			2.15								
29				icro HDMI to HDI	om/web/p/hdmi-c	5.56	2m			5.56								
30				Heatshrink	rink-sleeving-kit-	8.45	150pc			8.45								
31		Boards	Allow prototyping by plac															
32																		

Figure 22: Bill of Materials

FreeCAD System Design

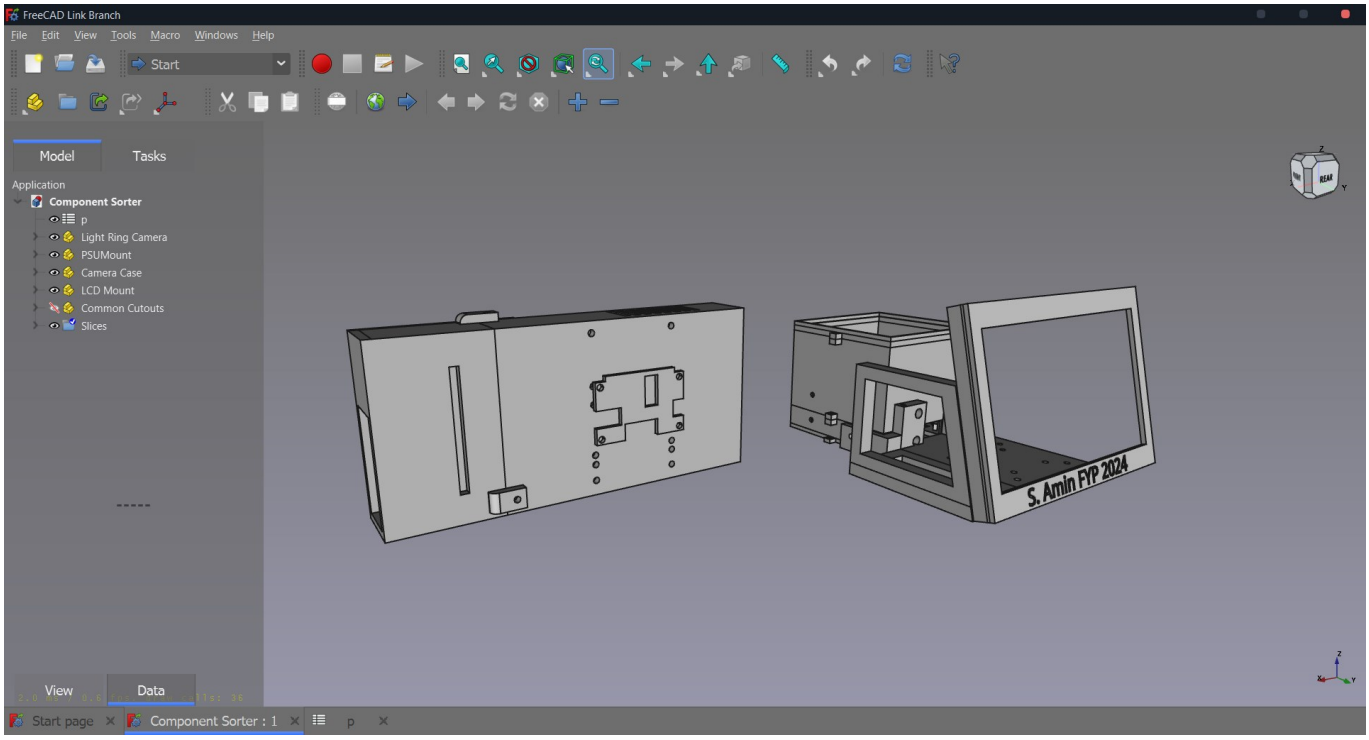

Figure 23: Stage 1 FreeCAD System Design

Raspberry Pi Benchmarking

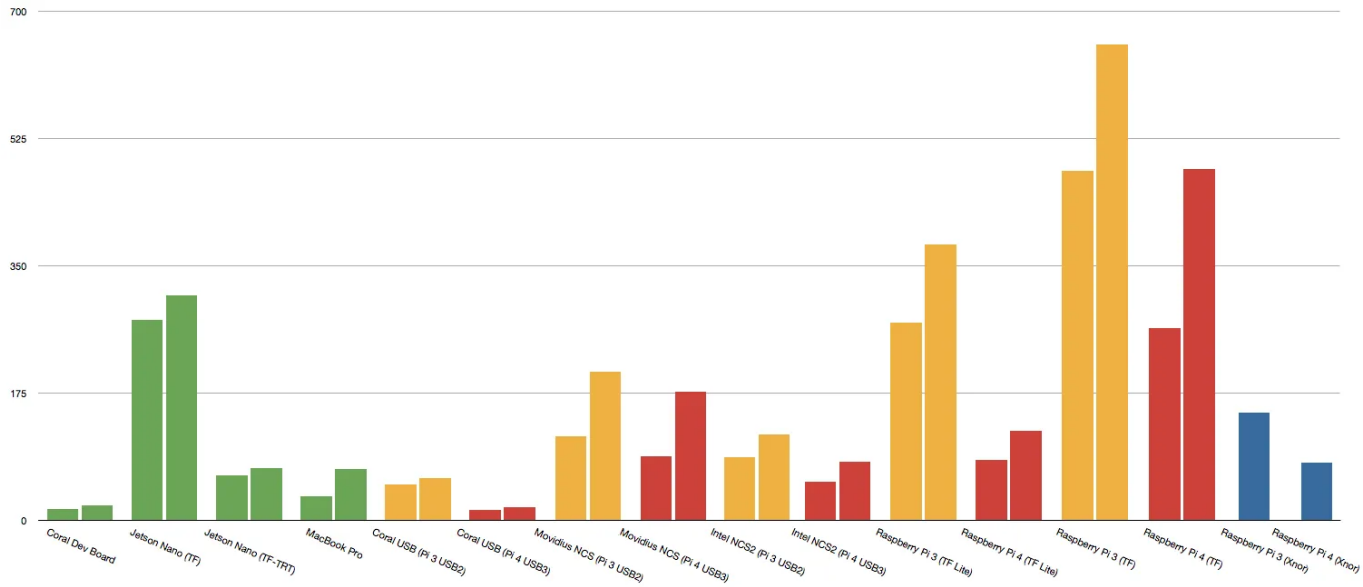

Figure 24: Raspberry Pi Benchmarking