Republic of Yemen
Ministry of higher Education and Scientific research
Emirates International University
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SMART MICROSCOPE

المجهر الذكي

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A graduation project report submitted to the department of
College of Engineering and Information Technology
Emirates International University
in partial fulfillmentof the requirements of bachelor degree in
BACHELOR OF SCIENCE IN BIOMEDICAL ENGINEERING

2023-2024

Summary

Microscopy, a fundamental tool in scientific exploration and research, has traditionally relied on manual operation, introducing inherent limitations in terms of precision, efficiency, and data analysis. The manual nature of microscopy often leads to inconsistencies in image acquisition, user fatigue, and time-consuming data collection processes. Moreover, the extraction of quantitative information from microscopic images is a labor-intensive task prone to human error and subjectivity, hindering the generation of reliable and reproducible results.

The manual operation of microscopes presents several critical challenges that hinder its effectiveness in modern scientific research. Human error, a prevalent issue in manual microscopy, impacts sample positioning, focusing, and image capture, leading to unreliable and biased data. Additionally, the time-consuming nature of manual microscopy, especially when dealing with large datasets or repetitive tasks, hampers productivity, limits the scope of research, and increases operational costs. Furthermore, manual image analysis is subjective and prone to inter-observer variability, making it challenging to extract quantitative data from complex microscopic images and hindering the ability to draw meaningful conclusions. The overall manual process bottlenecks the research workflow, impeding the ability to analyze large volumes of data and generate timely insights.

To address the limitations of manual microscopy, this research proposes the development of an automated microscopy system that integrates hardware and software components to enhance efficiency, accuracy, and data analysis capabilities. The system incorporates automated image acquisition, including stage movement, focus adjustment, and image stitching, to improve consistency and reduce human error. Advanced image processing techniques are employed to enhance image quality, reduce noise, and extract relevant features for subsequent analysis. To further augment the system's capabilities, artificial intelligence algorithms are utilized to perform complex image analysis tasks such as object detection, classification, and quantification. This includes the development of models specifically designed for tasks like malaria parasite detection and classification within blood smear images. A user-friendly interface facilitates interaction with the system and enables researchers to easily access and analyze the generated data. By addressing the challenges associated with manual microscopy, this automated system aims to revolutionize scientific research by providing researchers with a powerful tool for efficient data acquisition, analysis, and interpretation, ultimately leading to accelerated discoveries and advancements in various fields.

Dedication

As we stand together on this momentous occasion, we dedicate this project to the countless individuals who illuminated our path.

This journey wasn't a solo expedition, but a collaborative effort fueled by late nights, shared determination, and an insatiable thirst for knowledge. We are deeply grateful to our families and loved ones who provided unwavering support and unwavering belief in our collective dream. Their encouragement was the wind beneath our collective wings, propelling us forward even when the road seemed daunting.

A special debt of gratitude goes to Professor Dr. Waleed Al-Talabi, whose guidance, patience, and sharp critique provided invaluable direction. We also want to express our sincere appreciation to all our doctors and mentors who challenged us to think critically and push the boundaries of our understanding.

To our fellow graduates, this achievement is a testament to the power of collaboration. We shared countless study sessions, brainstormed until the wee hours, and celebrated each breakthrough with infectious enthusiasm. We learned the importance of communication, the strength that comes from diverse perspectives, and the sheer joy of discovery when shared with a supportive team.

Looking back, this journey feels like a whirlwind of emotions, filled with moments of collective doubt and moments of pure, unbridled joy. Most importantly, this project has taught us invaluable lessons about resilience, the importance of asking questions, and the sheer satisfaction of pushing beyond our perceived limitations as individuals and as a group.

So, as we stand at this milestone, we dedicate this project to all of you who have been our guiding light. Thank you for believing in us, even when we doubted ourselves, and for celebrating every step of the way. Here's to new beginnings and the exciting possibilities that lie ahead, together!

Acknowledgment

Before and above all, we would like to record our endless thanks to **Allah** for everything he gives us. We are eternally grateful for the countless opportunities for growth and knowledge He has bestowed upon us.

We would like to express our sincere appreciation and profound thanks to Dr. Waleed Al-Talabi for his invaluable guidance, encouragement, and scientific expertise. His constructive criticism, helpful supervision, and unwavering belief in our abilities were instrumental in shaping this project and propelling us forward. We are particularly grateful for Dr. Mohammed Al-Olfi, and his dedication to our success instilled within us the strength and motivation to overcome challenges and persevere through difficult moments.

We are also deeply grateful to our families for their unwavering support, encouragement, and unwavering belief in us. Their patience and understanding during countless late nights and moments of frustration were invaluable. Their constant love and support provided a safe haven and a source of strength throughout this journey.

Finally, we would like to extend our thanks to our friends and colleagues for their support and camaraderie throughout this endeavor. Their insightful discussions, shared experiences, and moments of laughter helped us maintain focus and provided a sense of community during challenging times. We are particularly grateful to Eng. AL Qassim Abdulkhaleg Rashed for his invaluable assistance in designing the whole project. His expertise in internal design was instrumental in overcoming a critical technical hurdle. His willingness to share his knowledge and collaborate with us significantly improved the functionality and design of the final product.

We are truly grateful to all of you for your contributions to this project. Your support and guidance have been instrumental in our success.

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Chapter 1

Introduction

Chapter 1: Introduction

1.1 Overview

Microscopy has revolutionized our understanding of the microscopic world, unveiling the intricate structures and processes that govern biological and material systems. From the delicate dance of chromosomes during cell division to the intricate microstructure of materials, microscopes have empowered researchers to explore and unravel mysteries beyond the naked eye.

However, conventional manual microscopes, while indispensable tools for observation, often pose limitations that hinder their effectiveness in modern scientific endeavors. The reliance on manual operation introduces inherent challenges in terms of precision, user fatigue, and data acquisition. Manual focusing and adjustments can lead to inconsistencies in image quality and data accuracy, especially during prolonged observation sessions. The strain of manual operation can result in eye fatigue and reduced concentration, affecting the quality of observations and the researcher's ability to maintain focus. Additionally, manual data collection is time-consuming and prone to errors, hindering efficient analysis and interpretation of the vast amount of information generated by microscopy experiments.

Unveiling a new era of microscopic exploration, AI analysis steps onto the scene, wielding its own powerful tools. No longer solely reliant on human observation, automated microscopes can now leverage the unmatched speed and precision of AI algorithms.

1.2 Problem Statement

Manual microscopy presents several distinct challenges that limit its efficiency and effectiveness in research settings:

Error-prone processes: Studies have documented the susceptibility of manual microscopy to human error, particularly in sample positioning. Inaccuracies can occur during slide manipulation, leading to inconsistencies in data collection [1].
Time constraints: The time-consuming nature of manual focusing and image capture can pose a significant challenge in high-throughput research environments. Repetitive tasks can significantly hinder the rate of data acquisition [2].
Limited data analysis: Manual analysis of microscopic images can be subjective and prone to bias. Additionally, extracting quantitative data from complex microscopic features can be a laborious process.
Critical Need for Malaria Parasite Classification: The inability to efficiently distinguish between different Plasmodium species hinders malaria prevention, treatment, and eradication efforts, emphasizing the critical role of accurate parasite classification in reducing the global malaria burden.

1.3 Project Objectives

Fortunately, advancements in automation technologies have opened doors to integrating them with microscopy. This convergence has revolutionized the field, offering substantial benefits:

- Enhanced Throughput: Automation streamlines sample analysis and image acquisition. By automating stage movement and image capture, researchers can collect data sets significantly faster, accelerating the pace of discovery [3].
- Improved Reproducibility: Standardized automated processes minimize human error, ensuring consistency and reliability in results. This reduces variability and strengthens the foundation for scientific conclusions [4].
- Advanced Data Analysis: Integration with image analysis software empowers researchers with objective quantification of microscopic features. This allows for the extraction of valuable metrics and deeper insights from the captured images [5].
- Reduced Fatigue: By automating repetitive tasks like focusing and image capture, researchers are relieved from manual strain. This allows them to focus on data interpretation, experiment design, and scientific discovery [6].
- Assistance in providing the number of informants in remote areas.
- Easy view full photos of the slice.
- Reduce the cost to the patient and medical centers by providing the effort to find images for informants.
- Automation**:** Streamlining workflows and data collection.
- AI analysis**:** Enhancing analysis speed, objectivity, and depth of insights.

This project is driven by the ambitious objective of transforming a standard manual microscope into an automated system. This will be achieved by incorporating suitable automation technologies to augment its functionalities, address the limitations outlined above, and leverage AI for intelligent image analysis. The overarching goal is to create a more efficient, reliable, and data-rich microscopy experience.

1.4 Project Scope and Limitations

The scope of this project encompasses the automation of a standard light microscope and the implementation of essential image processing techniques. The project will focus on automating basic microscope operations and image enhancement, while more advanced image analysis and machine learning applications may be considered in future extensions.

1.5 Project Methodology

To achieve the project objectives and deliver a functional automated microscope system, a structured methodology will be employed, comprising the following phases:

1. System Design: Carefully design the architecture of the automated microscope system, meticulously considering hardware components, software modules, and communication protocols. This phase will lay the foundation for a robust and integrated system.

2. Hardware Integration: Seamlessly integrate hardware components, including motorized stages, cameras, and data acquisition devices, into the system. This integration will ensure efficient data acquisition and control of microscope operations.

3. Software Development: Develop comprehensive software modules for automated microscope control, image processing, and data management. These modules will provide the system with the intelligence and functionality to perform its intended tasks, also developing AI software specifically designed for analyzing microscopic images. This software will revolutionize image analysis by leveraging machine learning and deep learning algorithms.

4. System Testing and Evaluation: Conduct rigorous testing and evaluation procedures to ensure the system's functionality, performance, and reliability. This rigorous testing will identify and address potential issues, ensuring the system meets the project's objectives.

5. Documentation: Prepare comprehensive documentation covering system design, implementation details, testing procedures, and user manuals. This documentation will serve as a valuable resource for future users and maintainers of the system.

1.6 Report Organization

This report is structured to provide a comprehensive overview of the project, encompassing the following chapters:

Chapter 1: Introduction (you are reading it now)
Chapter 2: Literature Review: Examines existing literature on automated microscopy systems, focusing on relevant advancements and addressing similar projects.
Chapter 3: Project Design: Details the technical design of the automated microscope system, including hardware selection, software architecture, and communication protocols.
Chapter 4: Describes the assembly process of the automated microscope system, outlining the steps involved in hardware integration, software installation, and configuration. A crucial aspect will be the development and integration of training modules for the AI software. These modules will provide the AI with the necessary training data to effectively analyze microscopic images.
Chapter 5: Results and Discussions: Presents the results obtained from system testing and evaluation, along with a comprehensive discussion of the findings. This chapter will analyze the system's performance, identify any limitations, and compare the results to project objectives.
Chapter 6: Conclusions and Recommendations: Summarizes the key findings of the project, highlighting its achievements and limitations. This chapter also provides recommendations for future improvements and potential extensions to the automated microscope system.

Chapter 2

Background and Literature Review

Chapter 2: Background and Literature Review

2.1 Background

Microscopy has revolutionized our understanding of the microscopic world, enabling researchers to visualize and study structures that are invisible to the naked eye. The invention of the first compound microscope in the 17th century marked a turning point in scientific advancements, providing scientists with a powerful tool to observe and unravel the intricacies of the biological, medical, and material realms. Manual microscopes, with their simple and robust design, have been the mainstay of microscopy for centuries, serving as indispensable instruments in educational settings, research laboratories, and clinical practice. their limitations are giving way to a new era – AI-powered automated microscopes. These intelligent image analysis machines promise faster, more objective, and deeper insights, pushing the boundaries of scientific exploration.

2.1.1 Types of Manual Microscopes

The realm of manual microscopy encompasses a diverse range of instruments, each tailored to specific applications and offering unique advantages. Some of the most prevalent types of manual microscopes include:

1. Light Microscopes: Light microscopes utilize visible light to illuminate the sample, providing a direct and intuitive view of microscopic structures. They are the most widely used type of microscope, finding applications in a vast array of disciplines, including biology, medicine, and material science.[7] Light microscopes can be further categorized based on their magnification capabilities:

a. Simple Light Microscopes: These microscopes offer a basic magnification range, typically between 4x and 10x, making them suitable for observing larger cells, tissues, and microorganisms.

b. Compound Light Microscopes: Compound light microscopes combine multiple lenses to achieve higher magnifications, typically ranging from 40x to 1000x.[8] They are employed for examining finer details of cells, organelles, and other microscopic structures.

2. Electron Microscopes: Electron microscopes harness the power of electrons to illuminate the sample, surpassing the diffraction limit of light microscopy and achieving resolutions that are orders of magnitude higher. They are particularly valuable for studying ultrastructural details of cells, viruses, and nanoparticles.

a. Transmission Electron Microscopes (TEMs): TEMs transmit electrons through a thin sample, generating high-resolution images of internal cellular structures.

b. Scanning Electron Microscopes (SEMs): SEMs scan the surface of a sample with electrons, producing detailed three-dimensional images of its topography and morphology.

3. Scanning Probe Microscopes: Scanning probe microscopes employ a physical probe, such as an atomic force microscope (AFM) or scanning tunneling microscope (STM), to interact directly with

the sample surface. They offer unparalleled resolution, capable of imaging individual atoms and molecules.

2.1.2 Applications of Automated Microscopy:

Automated microscopy systems have found wide-ranging applications in various fields, including:

Biological Research: Studying cell structure, dynamics, and interactions, including cell division, protein trafficking, and signal transduction pathways.[9]

Medical Diagnostics: Analyzing tissue samples for disease detection and monitoring, such as cancer diagnosis and tumor characterization.[10]

Materials Science: Investigating the microstructure and properties of materials, including defects, grain boundaries, and phase transitions.

Environmental Monitoring: Assessing the quality of air, water, and soil by identifying and quantifying pollutants and microorganisms.

2.1.3 Limitations of Manual Microscopy:

Despite its widespread use and undeniable contributions to scientific advancements, manual microscopy is not without its limitations. These limitations have prompted the development of automated microscopy systems to address the shortcomings of manual methods.

1. Time-consuming Image Acquisition: Manual image acquisition can be slow and tedious, especially when dealing with large samples or high-throughput experiments. This can significantly limit the amount of data that can be collected and analyzed.

2. Labor-intensive Analysis: Manual image analysis is often labor-intensive and prone to human error, particularly when analyzing large datasets or complex images. This can lead to inconsistencies in results and subjective interpretations.

3. Limited Reproducibility: The subjective nature of manual image analysis can result in limited reproducibility of results, making it challenging to compare findings across studies.[11]

4. Increased Risk of Human Error: Manual image acquisition and analysis are susceptible to human error, such as fatigue, distraction, and personal biases. This can introduce inaccuracies and inconsistencies into the data.

2.1.4 microscopic Organisms(Microbes):

A microbe, or “microscopic organism,” is a living thing that is too small to be seen with the naked eye. We need to use a microscope to see them.
The term is very general. It is used to describe many different types of life forms, with dramatically different sizes and characteristics:

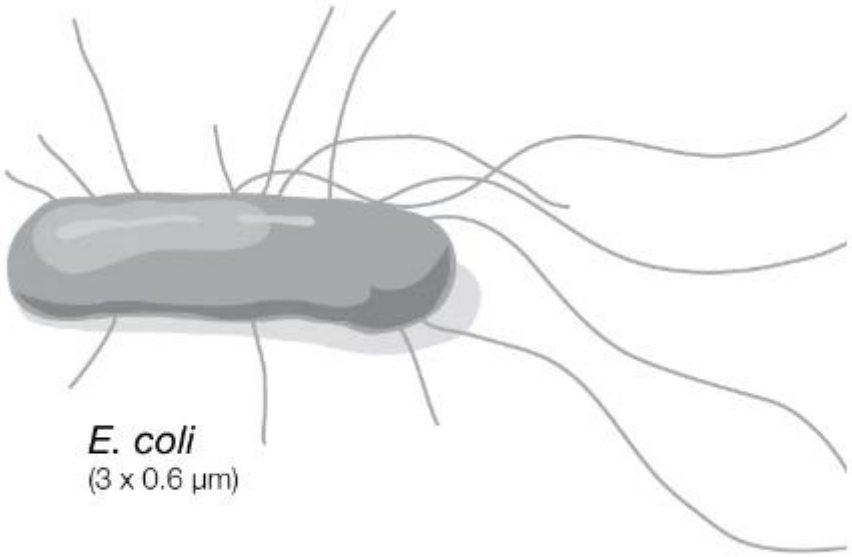
Bacteria:

Bacteria are microscopic, single-celled organisms that have no nucleus and a cell wall made of peptidoglycan. Bacteria are the direct descendents of the first organisms that lived on Earth, with fossil evidence going back about 3.5 billion years.

Most bacteria are much smaller than our own cells, though a few are much larger and some are as small as viruses. They usually do not have any membrane-wrapped organelles (e.g., nucleus, mitochondria, endoplasmic reticulum), but they do have an outer membrane. Most bacteria are also surrounded by at least one layer of cell wall.

Bacteria are a huge and diverse group. Its members have many shapes, sizes, and functions, and they live in just about every environment on the planet.

Figure 2 1 bacteria cell



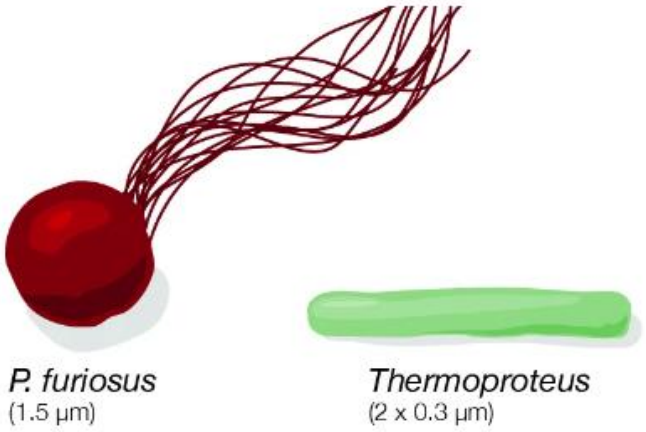
Archaea:

Archaea are microscopic, single-celled organisms that have no nucleus and an outer membrane containing unique lipids. On the surface, archaea look a lot like bacteria: they can have a similar size and shape, their genetic material forms a circle, they lack organelles, and they live in similar environments. But biochemically, archaea are as different from bacteria as they are from us.

Archaea are surrounded by a membrane made up of a type of lipid that isn't found in any other organism. Most archaea also have a cell wall, but theirs is very different from the peptidoglycan cell wall of bacteria.

Archaea are best known for living in extreme environments, but they also live in non-extreme environments, including the human gut and skin.

Figure 2 2 Archaea cell



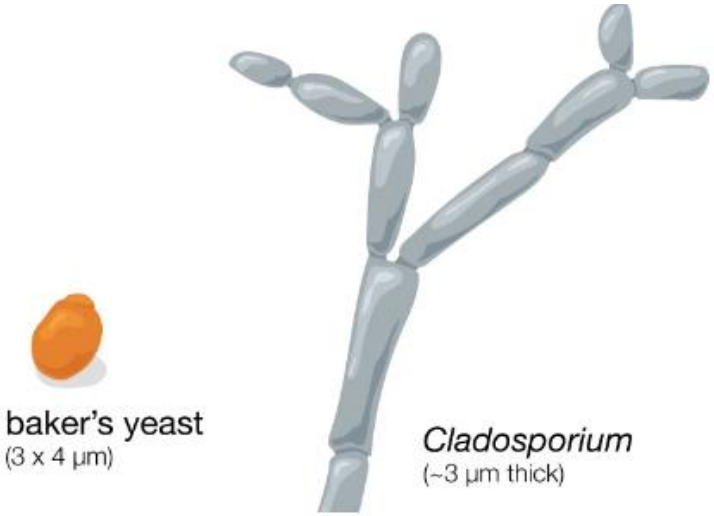
Fungi:

Fungi are single-celled or multicellular organisms with nuclei and with cell walls made of chitin. They also have membrane-wrapped organelles, including mitochondria. Unlike plants, fungi cannot make their own food.

Familiar fungi include yeasts, molds, and mushrooms. Yeasts live as small, individual cells, between the size of bacteria and our own cells. Molds and mushrooms are actually the fruiting bodies of fungi that live as long, microscopic fibers.

Fungi are important decomposers in most ecosystems. Their long, fibrous cells can penetrate plants and animals, breaking them down and extracing nutrients. Several species of fungi, mostly yeasts, live harmlessly on the human body.

Figure 2 3 Fungi cell



Protists:

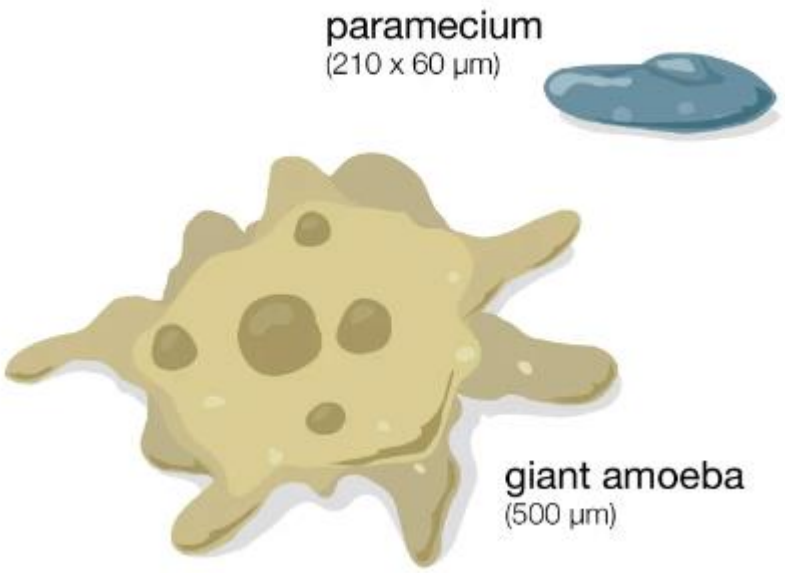
Protists are single-celled or multi-cellular, microscopic organism with cell nuclei, and which aren't

plants, animals, or fungi. Multi-cellular protists live as colonies, without specialization. Protists are a category of leftovers and oddballs that don't fit into other groups, and taxonomists are continually reorganizing them.

Because protists are defined more by what they don't have than what they do, they're a very diverse group. Some make their own food using chloroplasts, but most don't. They have many ways of moving around, including flagella, cilia, and amoeboid action. They have multiple ways of reproducing, and some have quite complex life cycles. But they have membrane-wrapped organelles and an outer cell membrane.

Several parasitic protists can cause deadly diseases, including malaria, amoebic dysentery, and giardia. But the human body is also home to beneficial and neutral protists.

Figure 2 4 Protists cell



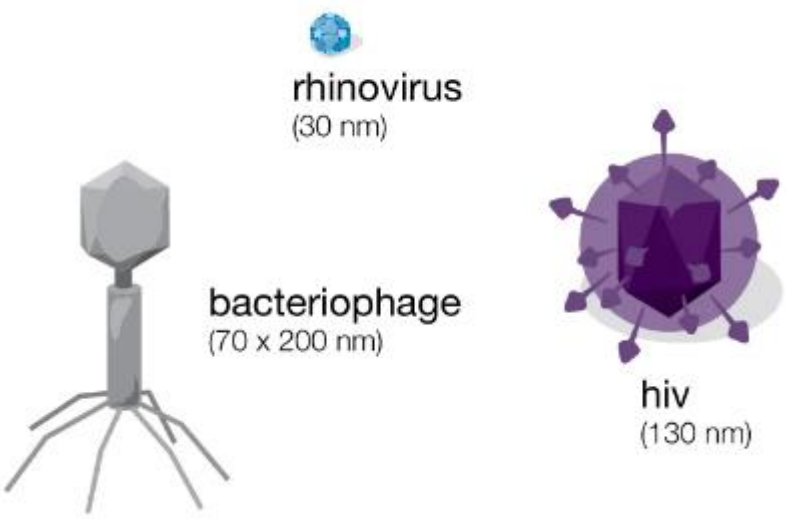
Virus:

Viruses are microscopic particles made of nucleic acids, proteins, and sometimes lipids. Viruses can't reproduce on their own. Instead, they reproduce by infecting other cells and hijacking their host's cellular machinery. Viruses are specialized to infect a certain host, and often a specific cell type within that host. HIV, for example, infects a certain type of immune cell in primates. Other viruses infect plants, animals, bacteria, or archaea.

Since the ability to reproduce is often listed as a requirement for life, some consider viruses to be non-living. Regardless, viruses are an important part of all ecosystems, including the human body.

In our bodies, viruses infect not only our cells, but also other microbes that live in our bodies. Viruses that infect bacteria are called baceriophage. Viruses that infect archaea come in unusual shapes: some have two tails, others are shaped like bottles or flowers.

Figure 2 5 Virus cell



The human body is home to microbes from all of these categories. Microscopic plants are also considered microbes, though they don't generally live on or in the human body.[12]

2.1.5 Malaria:

Malaria is a life-threatening disease spread to humans by some types of mosquitoes. It is mostly found in tropical countries. It is preventable and curable.

The infection is caused by a parasite and does not spread from person to person.

Symptoms can be mild or life-threatening. Mild symptoms are fever, chills and headache. Severe symptoms include fatigue, confusion, seizures, and difficulty breathing.

Infants, children under 5 years, pregnant women, travelers and people with HIV or AIDS are at higher risk of severe infection.

Malaria can be prevented by avoiding mosquito bites and with medicines. Treatments can stop mild cases from getting worse.

Malaria mostly spreads to people through the bites of some infected female Anopheles mosquitoes. Blood transfusion and contaminated needles may also transmit malaria. The first symptoms may be mild, similar to many febrile illnesses, and difficulty to recognize as malaria. Left untreated, P. falciparum malaria can progress to severe illness and death within 24 hours.

There are 5 Plasmodium parasite species that cause malaria in humans and 2 of these species – P. falciparum and P. vivax – pose the greatest threat. P. falciparum is the deadliest malaria parasite and the most prevalent on the African continent. P. vivax is the dominant malaria parasite in most countries outside of sub-Saharan Africa. The other malaria species which can infect humans are P. malariae, P. ovale and P. knowlesi.
People with severe symptoms should get emergency care right away. Getting treatment early for mild malaria can stop the infection from becoming severe.

Disease burden:

According to the latest World malaria report, there were 249 million cases of malaria in 2022

compared to 244 million cases in 2021. The estimated number of malaria deaths stood at 608 000 in 2022 compared to 610 000 in 2021.

The WHO African Region continues to carry a disproportionately high share of the global malaria burden. In 2022 the Region was home to about 94% of all malaria cases and 95% of deaths. Children under 5 years of age accounted for about 78% of all malaria deaths in the Region.

Four African countries accounted for just over half of all malaria deaths worldwide: Nigeria (26.8%), the Democratic Republic of the Congo (12.3%), Uganda (5.1%) and Mozambique (4.2%).

Treatment:

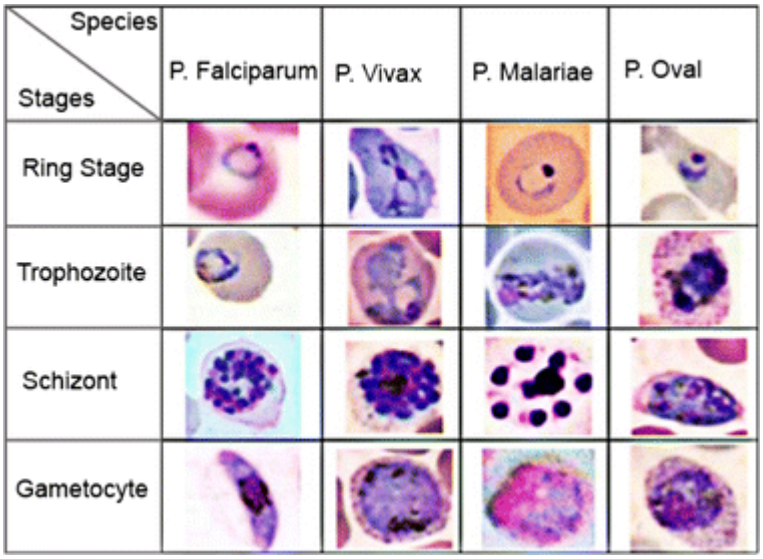
Early diagnosis and treatment of malaria reduces disease, prevents deaths and contributes to reducing transmission. WHO recommends that all suspected cases of malaria be confirmed using parasite-based diagnostic testing (through either microscopy or a rapid diagnostic test).

Malaria is a serious infection and always requires treatment with medicine.
Multiple medicines are used to prevent and treat malaria. Doctors will choose one or more based on:

- the type of malaria.
- whether a malaria parasite is resistant to a medicine.
- the specific stage of malaria (life cycle).
- the weight or age of the person infected with malaria.
- whether the person is pregnant.[13]

Here are the malaria parasite species and their stages (life cycle):

Figure 2 6 malaria parasite species and stages



2.2 Literature Review

The automation of microscope stages has been a topic of interest in recent years, with various studies focusing on different aspects of this technology.
The following studies focus on the part of microscope automation.

- Fiedler et al. Vega-Alvarado et al. (2020) The main limitation mentioned in the abstract is that the visual microscopic evaluation of stained blood smears to detect the Chagas parasite is a "tedious and time-consuming task that requires a trained operator". [14]

- Katunin et al. (2020) The main outcomes of this study is the development of an open-source, low-cost hardware framework for automating cell biology experiments, including features like an XY-stage, perfusion system, and fluorescent microscope. The framework is described as being highly customizable and suitable for a variety of biological applications.[15]

- Kim et al. (2020) explored the optimization of multiple microscope settings for automated image interpretation by computer algorithms, By jointly optimizing microscope settings and a classification network, the study aimed to improve performance in automated tasks such as feature classification and segmentation The key limitation mentioned in the abstract is that standard microscopes are often optimized for human interpretation, rather than for automated computer-based interpretation of microscope images. [16]

- Moreno et al. (2021) While newer solutions like Microscope provide a Python-based interface for controlling microscope devices, their GUI is still limited to simpler microscopes, indicating a limitation in handling more complex microscope setups.17]

- J. Collins (2022) introduced the Open Flexure Delta Stage, a 3D-printed microscope designed for researchers to perform automated routines and acquire images in various modalities.[18][19]

The following studies focus on the part of Image classification.

Table 2 1 Analyzing Literature Review

Authors	Methods	Results
Gitonga et al., 2014	Apply an ANN on segmented cells for parasite species classification.	**96.2% accuracy for ANN classifier.[20]**
Penas et al., 2017	Apply a CNN model for parasite species classification.	**87.9% accuracy for classification.[21]**
I. M. D. Maysanjaya et al., 2020	The use of two classification algorithms, Naïve Bayes and Perceptron.	**Naïve Bayes classifier achieved 97.29% accuracy for P. vivax, and 98.36% accuracy for P. falciparum.** **-Perceptron classifier achieved 81.08% accuracy for P. vivax, and 80.33% accuracy for P. falciparum.[22]**
Yasmin et al., 2021	The benchmark CNN classifiers.	**The final framework, after the Mask R-CNN detectors, achieved an overall accuracy of 90.8% on image level and 96.7% on patient level.[23]**
Dath et al., 2023	The use of various deep learning models (CNN, ResNet50, VGG19)	**The key result from the study is that the VGG19 with accuracy of 92.86%.[24]**

2.3 Challenges and Future Directions:

Despite the advancements in automated microscopy, challenges remain in achieving optimal performance and addressing specific application needs. These challenges include:

Developing more robust and efficient algorithms for image processing and analysis: Image processing algorithms are crucial for extracting meaningful information from raw image data. However, challenges remain in developing algorithms that are robust to noise, variations in lighting conditions, and complex sample structures.

Integrating machine learning techniques for automated image classification and segmentation: Machine learning algorithms can be employed to automate tasks such as image classification, segmentation, and object recognition. However, the success of these approaches depends on the availability of high-quality training data and the careful selection of appropriate algorithms.

Enhancing the interoperability of automated microscopy systems with other scientific instruments and data analysis tools: Integrated workflows that seamlessly connect automated microscopy systems with other scientific instruments and data analysis tools are essential for streamlining research processes and facilitating comprehensive analysis.

2.4 Conclusion: The Future of Automated Microscopy:

Automated microscopy has transformed the field of microscopy, providing researchers with powerful tools to study the microscopic world with unprecedented precision and efficiency. As technology continues to evolve, automated microscopy systems are poised to play an even more significant role in scientific discovery and innovation. Future advancements in image processing, machine learning, and data management will further enhance the capabilities of automated microscopy systems, enabling researchers to tackle increasingly complex challenges and make groundbreaking discoveries across various scientific disciplines.

2.5 Potential Impact of Automated Microscopy:

Automated microscopy systems have the potential to revolutionize various fields by:

Accelerating scientific research: By automating time-consuming tasks and enabling high-throughput data acquisition, automated microscopy systems can significantly accelerate the pace of scientific research.

Improving data quality and consistency: Automated systems can minimize human error and ensure consistent image acquisition and data collection, leading to higher data quality and reproducibility.

Enabling new discoveries: By providing researchers with the ability to collect and analyze large datasets efficiently, automated microscopy systems can facilitate the discovery of new phenomena and insights.

Promoting collaboration and data sharing: Open-source software and standardized data formats can promote collaboration among researchers and facilitate the sharing of data, leading to faster progress and innovation.

Chapter 3

Project Design

Chapter 3: Project Design

3.1 Introduction

This chapter dives deep into the hardware components that form the foundation of this project. We'll meticulously dissect each component, exploring its functionalities and how it interacts with the others to form a cohesive system.

3.2 Hardware components :

This section meticulously details the essential hardware components that form the foundation of this project. Each component will be meticulously dissected, outlining its functionalities and its role within the larger system.

3.2.1 Microscope:

This is the main component that this project built on to be able for accepting the automation parts and easy to be modified.
To achieve these specifications, we decided to use the OLYMPOS CH2 microscope and here is the product properties and some features.

Figure 3 1 OLYMPOS CH2

The BH2 model was released in an attempt to build upon the already successful Olympus BH microscopes. The goal of the BH2 was superior optics and ease of customization, and it soon became very well known for both.[25]

Product features:

- It comes with the highly favored Olympus BH2 stand.
- Eyepieces that magnify to both 10x and 20x.
- A nose piece that can be moved into one of five positions.
- Pre-set light feature.
- An Abbe condenser with 1.25 iris.
- A stage that has both coarse and fine adjustment.
- A slide holder with a XY rack and pinion adjustment.
- Weighs twenty-four pounds.
- Extremely customizable.
- Olympus then developed a long barrel (LB) objective lens series (1x–100x oil) with a focal length of 45 mm.

3.2.3 lmage Acquation:

In the realm of microscopy, where the unseen becomes visible, choosing the right camera is crucial. The SONY IMX307 camera emerges as a compelling option, boasting a high-resolution sensor and versatile connectivity features. This camera seamlessly integrates with your existing microscope setup, thanks to its standard C-Mount lens mount.

Delving deeper, the IMX307 sensor captures intricate details of microscopic specimens, delivering crisp and informative visuals. Multiple output options, including HDMI and USB, provide flexibility for displaying the magnified view on a monitor or capturing images and videos directly to a computer.

While the SONY IMX307 excels in visualization, it's essential to consider the automation aspects of your project. For basic observation, this camera is a great choice. However, if your project demands more advanced automation features like programmatic control of focus or image capture, further exploration of microscope cameras with dedicated automation software development kits (SDKs) might be necessary.

Figure 3 2 Sony IMX307

Table 3 1 properties of SONY IM307

property		explanation
Summary	Sensor	SONY IMX307 (good low-light performance)
	Resolution	Discrepancy in listing - 48MP or 50MP (photo), 2K video, VGA, 1080p
	Connectivity	HDMI, VGA (external monitors), USB (computer), TF card (storage)
	Lens Mount	C-Mount (compatible with various objective lenses)
	Potential Uses	Phone/tablet repair, PC repair, PCB inspection, IC soldering
Limitations for Automation		Lacks information on software compatibility or automation features (zoom, focus, exposure control)
Better Option for Automation Project		Consider microscope cameras designed for automation with SDKs for integration
Additional Points		• Check compatibility with your microscope and software • Look for features like triggering, focus stacking, image stitching (if needed) • Consider price vs. features needed for your automation

In addition to the previous product, we added 0.5X C-Mount Lens CTV Camera Adapter for Simul Focal Trinocular Microscope HDMI VGA Video microscopic Camera Adapter Lens. This lens reduces the magnification by a factor of 0.5 compared to the direct view through the eyepiece. It allows for capturing a wider field of view at the sensor of the camera attached to the trinocular port.

Figure 3 3 0.5X C-Mount Lens

We can mention the advantages in the table 3.2.

Table 3 2 Advantages of 0.5x c-mount lens

Advantage	explanation
Expanding the Field of View	By incorporating the 0.5X C-Mount Lens CTV Camera Adapter alongside the SONY IMX307 camera, you can capture a wider field of view at the microscope's higher magnifications. This allows you to observe a larger area of the specimen while retaining high-resolution detail thanks to the SONY IMX307 sensor.
Seamless Integration	The C-Mount design of both the adapter and the camera ensures a perfect fit. The adapter connects seamlessly to the trinocular port of your microscope, allowing you to mount the SONY IMX307 camera effortlessly.
Enhanced Visualization	The combination of the 0.5X C-Mount Lens CTV Camera Adapter and the SONY IMX307 camera unlocks a powerful visualization experience. You can observe the magnified view through the microscope's eyepieces while simultaneously capturing high-quality images and videos on the external monitor connected via the adapter's HDMI or VGA output.
Flexibility for Different Observation Needs	This combined setup offers flexibility. Switch between the wider field of view provided by the 0.5X adapter for context or zoom in using the microscope's eyepieces for capturing intricate details, all while having the SONY IMX307 camera ready to document your observations.

3.2.4 Illumination:

There are many choices when buying a microscope in the 21st century and “lighting” is one of them. In this section, we look at the differences between LED and Halogen lighting to assist you with the best outcome for this application.

Led Lighting:

LED (Light Emitting Diode) is the latest technology with many advantages. They consume very little power, the bulbs last for a long time, and they can be paired with a rechargeable battery system making the scope cordless, enabling the users to take the microscope away from an external power source. LEDs made their first appearance on student microscopes; however, they are becoming more and more popular on professional microscopes. The LEDs with only on/off switch are usually too bright, making them inconvenient to use. It is a good idea to make sure your LED microscope has a potentiometer (Dimmer Knob) so you can reduce the light intensity. Recent technology advances have made these bulbs brighter, much more reliable, and fully dimmable.

Halogen Lights:

Halogen lamps provide a very white, bright, concentrated light, and are preferred on medical and lab instruments. Such scopes are usually fitted with a dimmer, which can as assist in reduction of heat. Halogen bulbs are extremely sensitive to skin oils, which can cause them to malfunction or burst. They last approximately 3,600 hours but are not as efficient as compact fluorescent lamps (CFL) or LED bulbs.

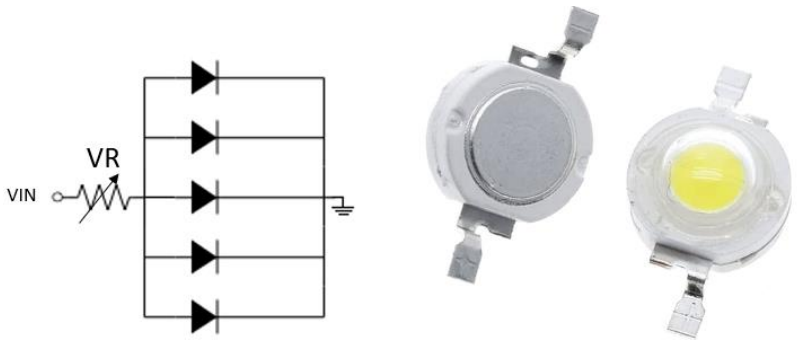
Led VS Halogen:

Table 3 3 LED VS HALOGEN [26]

property	Led	Halogen
Economics	An LED bulb is quite small; therefore, they are usually used in groups. They are often built into newer machines and depending on the connection, they can take longer to	A traditional style bulb. They are usually easy to use and the bulb is simple and low cost to change.

	replace. Although LEDs are normally more expensive than halogen bulbs, they are more energy-efficient and usually last substantially longer.	
Longevity	LED bulbs have good longevity and are quite reliable. The average life of an LED bulb is around 50,000 hours and die in an unpredictable and often spectacular way. They tend to burn out suddenly and without much warning	lasts approximately 3,600 hours and age in a predictable manner. It will be noticed that the bulb starts to throw different colors of light.
Light Color	lights are brilliant white and LED images tend to publish better as they are brighter.	white light when it is new and the light starts to become more yellow as it starts to age
Safety and Comfort	LED illumination makes for a safer and more comfortable specimen viewing session for the users by producing light waves that are outside the UV spectrum	Working with Halogen lamps can lead to quicker eye fatigue, discomfort, and possible long-term damage for users because Halogen lamps produce light waves within the UV spectrum

Figure 3 4 Led array & Led shape



The previous figure showing the illumination way used in our microscope where VIN = 3.5V
The VR can be set using Arduino controller to adjust the suitable value which control the intensity of led lights in each situation. The picture of led on the right side represent each diode in the circuit.

Figure 3 5 Stepper motor (NEMA 17)

3.2.5 Motorized Stage:

This section described how the manual stage converted into an automatic one.
To implement this purpose let us talk about Nema17 motor and its specifications.

Table 3 4 NEMA 17 Specification

Specification	Range
Current	1.5A to 1.8A per phase
Voltage	1v to 4v
Torque	44 N·cm (62oz·in, 4.5kg·cm) or more holding torque
inductance	3 to 8mH per phase
Steps	1.8 or 0.9 degrees per step (200/400 steps/rev respectively)

After talking about motors, we need to installation them to the microscope.
This part cannot be done without the 3D printer which designed the whole components in each axis this printer is **Creality Ender-3:**

Figure 3 6 Creality Ender-3(3D printer)

In addition to the printer, we need a filament with a perfect properties of its function and use. The filament with a perfect specification is ABS Filament. Let us mention some of them.
Acrylonitrile butadiene styrene (ABS) is the second most commonly used filament. ABS 3D printer filament has moderate strength and flexibility, and it features superior melt flow characteristics. ABS has a high heat tolerance, which allows it to withstand hot temperatures, but where it really shines is its durability. This filament is ideal for items that are frequently handled, dropped, or heated. These high-quality ABS material properties make this the right choice for general-purpose printing.
There are many versatile ways to use ABS material, but it's often found in household goods, such as LEGO bricks, office supplies, and bike helmets! Products made of ABS 3D printer filament are extra tough. They can survive high-heat conditions and multiple impacts. When printing, users should remember the high printing temperatures may lead to warping as products cool. A heating bed should take care of this problem. We sell ABS filament in 1.75mm and 2.85mm diameters. Example products include phone cases, high-wear toys, tool handles, automotive trim components,

and electrical enclosures.[27]

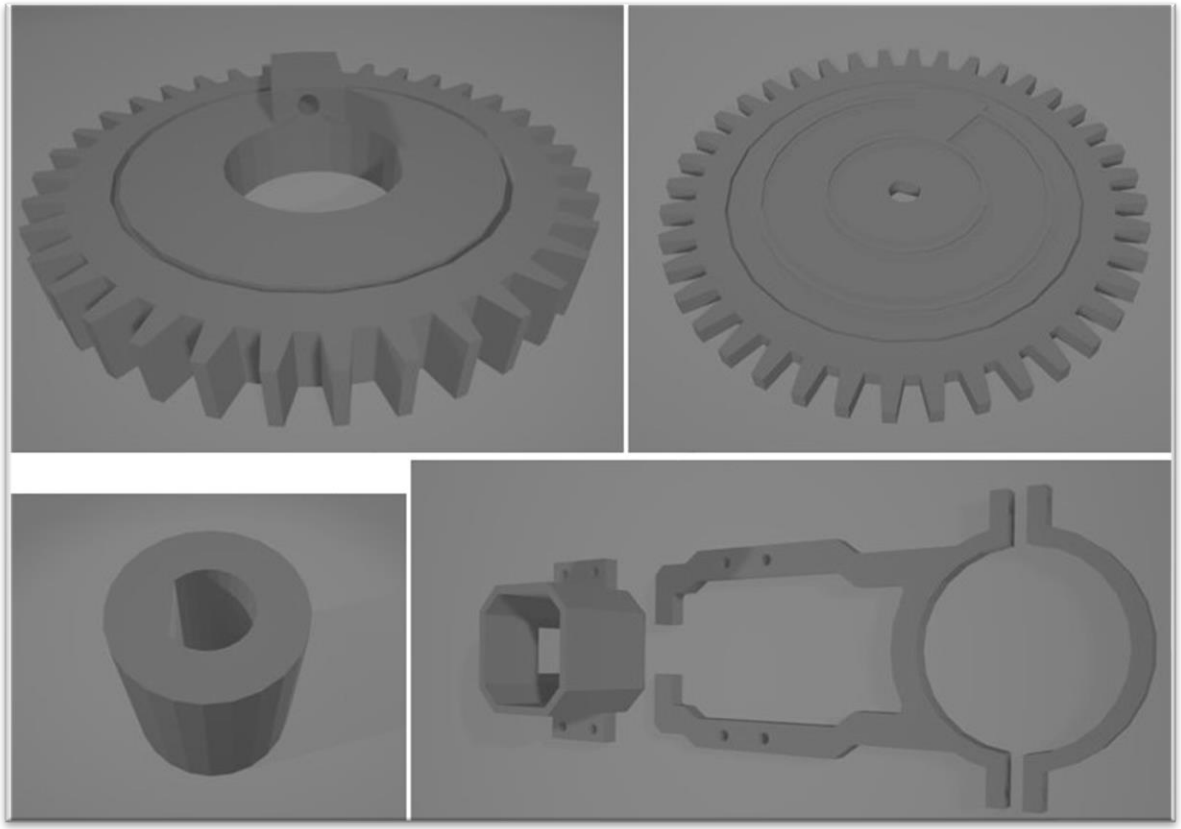
Now let us talking about the stage from the 3 axis and the designed parts of each one.

1. Z-Axis 2. Y-Axis 3. X-Axis

Z-Axis:

This axis is responsible of moving stage up and down or in another words it is the axis which controlling the focus of microscope. The motor installed above the fine and coarse knobs. The previous design holding motor and following gears connecting motor with knob.

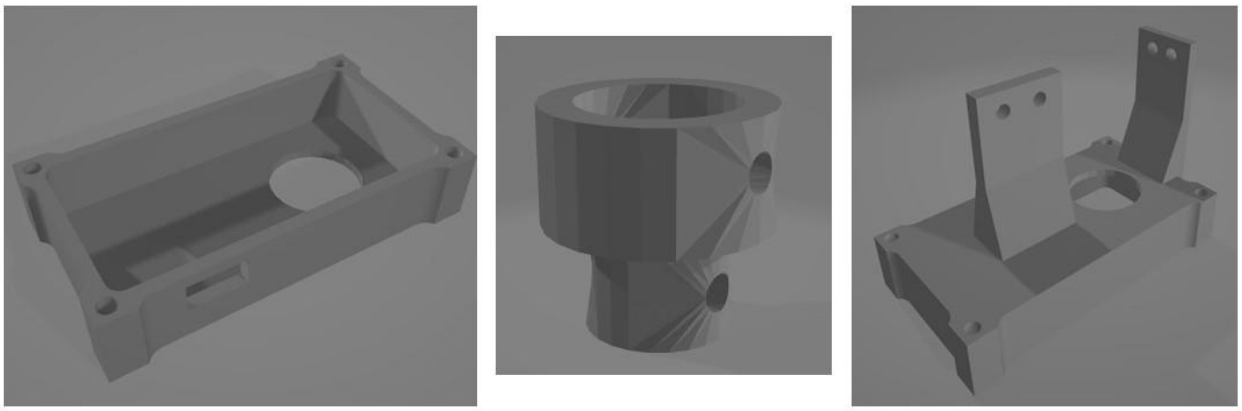
Figure 3 7 motor holder and gears of Z-Axis



Y-Axis and X-Axis:

These axes are responsible of moving stage right, left, forward and backward. Motor holders installed under the stage and connecting to the mechanical stage controllers by using timing belt.

Figure 3 8 motors and gear holders of X and Y Axis



3.2.6 Power Supply:

The heart of any electronic project is its power supply. It provides the stable and regulated electrical energy needed for project creation to function.

What a Power Supply Does?
It Converts AC to DC: Most electronic components require Direct Current (DC) to operate. The power supply takes the Alternating Current (AC) from the wall outlet and converts it into the required DC voltage.
Regulates Voltage: The voltage level needs to be precise for your components to function properly. The power supply regulates the DC voltage to ensure it remains constant, even with fluctuations in the AC input.
Provides Current: The power supply also delivers the necessary amount of current (amperage) to power project. Components have specific current needs, and the power supply must be able to deliver enough to operate them all.

Before choosing the type of power supply let us mention the components of this project.

Table 3 5 project components voltage and current

Component	No.	Voltage	Maximum current
Stepper motor (NEMA17)	4	12V	1.8A * 4 = 7.2A
Led	1	12V	200mA
Cooler Fan	1	12V	100mA
Total		12V	7.5A

In this project the suitable type according to the previous table is SMPS metal case power supply.

Figure 3 9 SMPS metal case

The following table showing the specifications of Metal case:

Table 3 6 specifications of SMPS [27]

Specification	Explanation
Input voltage	110 to 220V AC
Output voltage	12V DC
Output current	10A
Power rating	120W
Frequency	50HZ/60HZ
Protection	Inbuilt over voltage, over current, and short circuit
Use Design	Simple and easy
Response	Fast transient

3.2.7 RAMPS Assembly Guid:

After using the previous power supply, we should use another component to regulate the volt and current to the other components.

The RAMPS 1.4 Assembly Guide is the case which can presenting the regulation and advantages that can help in this project.

What is RAMPS case?

RAMPS 1.4 is probably the most widely used electronics for RepRap machines as of March 2014. It consists of a RAMPS 1.4 shield, an Arduino Mega 2560 board (or a clone), and a max of five Pololu Stepper drivers. It can control up to 5 stepper motors with 1/16 stepping precision and interface with a hot end, a heat bed, a fan (or a second hot end), a LCD controller, a 12V (or 24V with appropriate modification) power supply, up to three

thermistors, and up to six end stoppers.

Figure 3 11 RAMPS 1.4 Assembly Guide

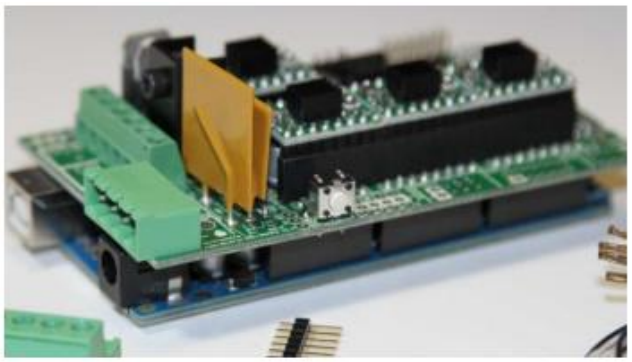
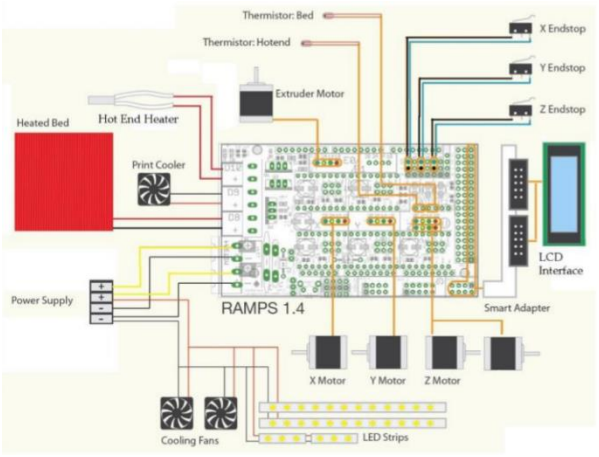


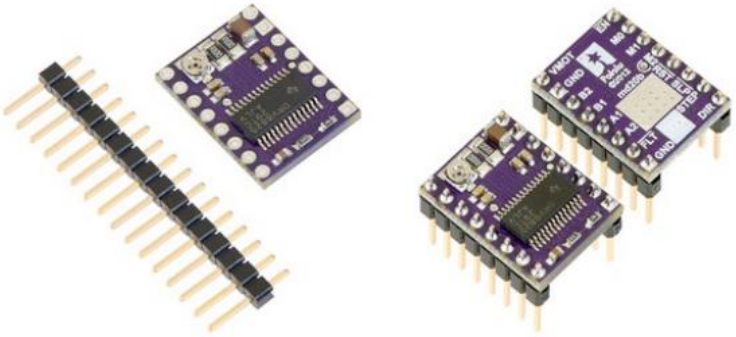
Figure 3 10 RAMPS 1.4 Schematic



3.2.8 DRV8825:

To connect motors with steppers, motors cannot connect directly without drivers connecting between power supply and the orders which coming from microcontroller.
The perfect drivers of NEMA17 motors is DRV8825 Stepper Motor Driver Carrier.

Figure 3 12 DRV8825

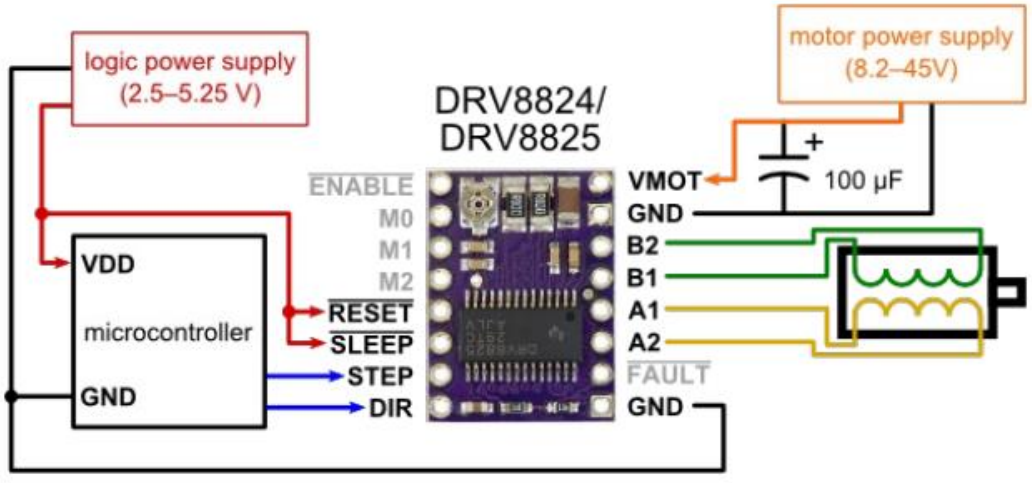


Here are some key features of this device:

- Simple step and direction control interface.
- Six different step resolutions: full-step, half-step, 1/4-step, 1/8-step, 1/16-step, and 1/32-step.
- Adjustable current control lets you set the maximum current output with a potentiometer, which lets you use voltages above your stepper motor's rated voltage to achieve higher step rates.
- Intelligent chopping control that automatically selects the correct current decay mode (fast decay or slow decay).
- 45 V maximum supply voltage.
- Built-in regulator (no external logic voltage supply needed).
- Can interface directly with 3.3 V and 5 V systems.
- Over-temperature thermal shutdown, over-current shutdown, and under-voltage lockout.
- Short-to-ground and shorted-load protection.
- 4-layer, 2 oz copper PCB for improved heat dissipation.
- Exposed solderable ground pad below the driver IC on the bottom of the PCB.
- Module size, pinout, and interface match those of our A4988 stepper motor driver carriers in most respects (see the bottom of this page for more information).[data sheet]

The Figure 3.13 is the wiring diagramfor connections:

Figure 3 13 wiring diagram connections



3.2.9 Endstops:

Also in this project we need to limit the range of movememt distance for each motor using endstops or end switches.
An end stop is a physical switch or sensor that detects when a moving part has reached its limit. This is common in machines with moving components, such as 3D printers or robotic arms. There are two main purposes for end stops in mechanics:

- **Safety:** They prevent damage by stopping the motor or actuator before the moving part hits a physical obstruction.
- **Homing:** They help the machine determine its current position by identifying the known maximum or minimum point of an axis.

Figure 3 14 end stops

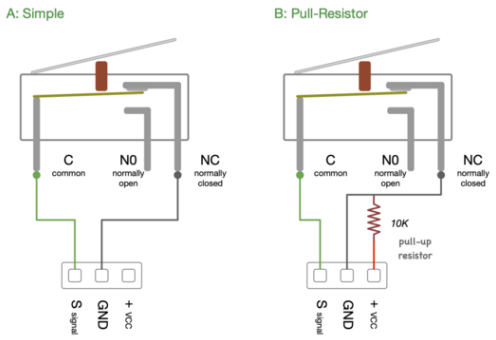


Figure 3 15 end stops circuit diagram

3.2.10 Timing pulley:

A timing pulley is a cogged or cross-tooth pulley with the belt tooth matching the pulley tooth, much like a chain and sprocket. U.S. Rubber developed the first timing pulleys or synchronous pulleys and belts in the 1940s. As the name synchronous implies, timing pulleys were first used to keep two shafts in synchronous. It is in the last 60 years that the timing pulley and belt are considered a positive drive alternative to chain and a replacement for friction drives, such as V-belts.

We at Torque Transmission continue to improve upon this tradition with our time-tested, precise, and reliable timing pulley solutions.
Advantages:
Timing Pulleys come with many distinct advantages, such as…

- Timing Pulley/Belts are a positive drive for the transfer of rotary mechanical force.

- Low backlash drive, high resolution for motion control applications, as well as low maintenance for continuous operations

- Positive drive for high torque load transmission applications, giving dependable service life, speed ratios, and low noise.

Figure 3 16 timing pulley

- Efficient operation and repetitive, accurate positioning

3.3 Microcontroller Unit (MCU) :

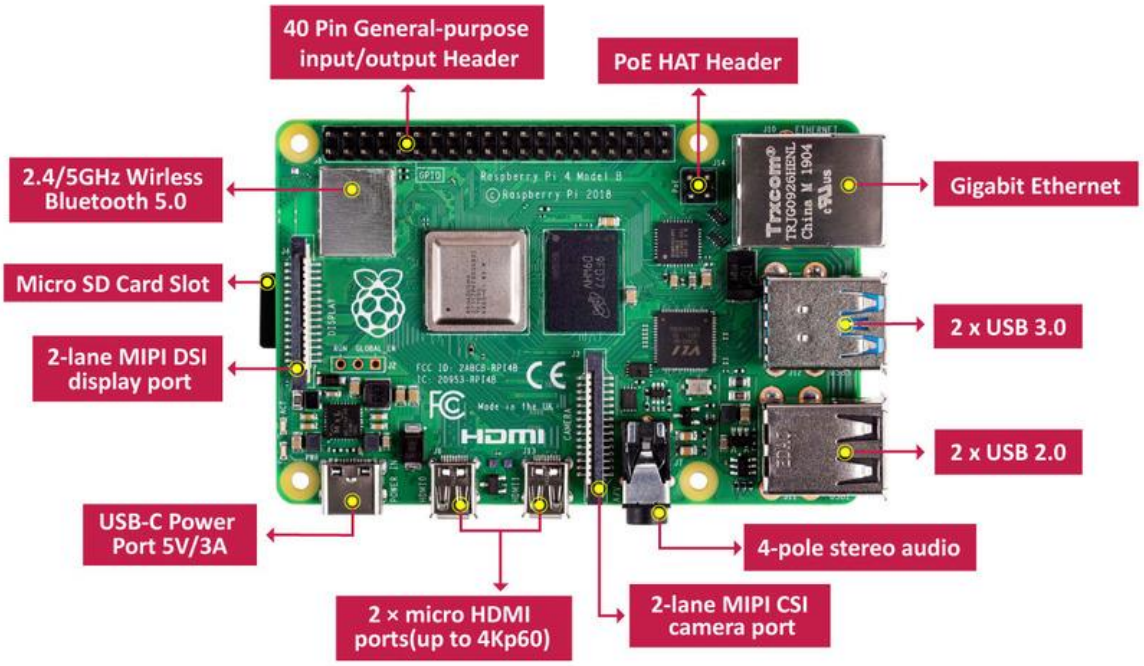
The brains behind the operation, it takes center stage in this section. We'll delve into its functionalities, exploring how it executes instructions, processes data, and interacts with the surrounding hardware components.

3.3.1 Raspberry Pi 4:

Raspberry Pi 4 Model B is the latest product in the popular Raspberry Pi range of computers. It offers ground-breaking increases in processor speed, multimedia performance, memory, and connectivity compared to the prior-generation Raspberry Pi 3 Model B+, while retaining backwards compatibility and similar power consumption. For the end user, Raspberry Pi 4 Model B provides desktop performance comparable to entry-level x86 PC systems.

This product’s key features include a high-performance 64-bit quad-core processor, dual-display support at resolutions up to 4K via a pair of micro-HDMI ports, hardware video decode at up to 4Kp60, up to 8GB of RAM, dual-band 2.4/5.0 GHz wireless LAN, Bluetooth 5.0, Gigabit Ethernet, USB 3.0, and PoE capability (via a separate PoE HAT add-on).
The following figure show the product with I/O ports:

Figure 3 17 Raspberry Pi 4



3.3.2 Arduino Mega 2560:

The Arduino Mega 2560 is a microcontroller board based on the ATmega2560. It has 54 digital input/output pins (of which 15 can be used as PWM outputs), 16 analog inputs, 4 UARTs (hardware serial ports), a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started. The Mega 2560 board is compatible with most shields designed for the Uno and the former boards Duemilanove or Diecimila.

Figure 3 18 Arduino Mega

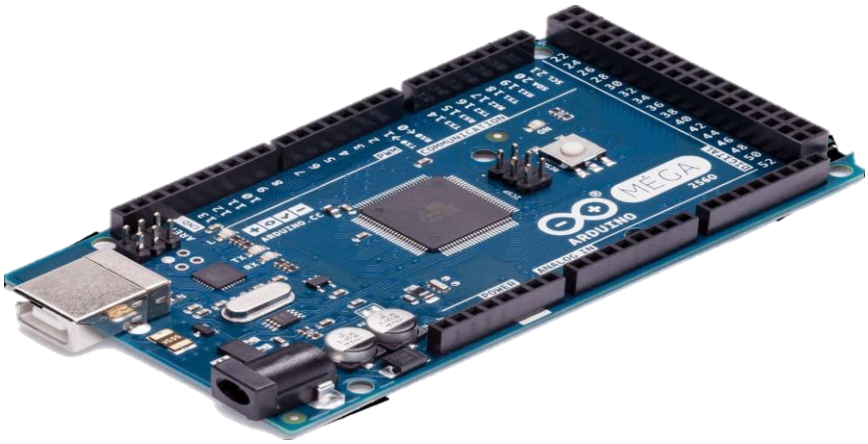


Table 3 7 Features of Arduino Mega 2560

Feature	**properties**
ATmega2560 Processor	Up to 16 MIPS Throughput at 16MHz. 256k bytes (of which 8k is used for the bootloader) 4k bytes EEPROM 8k bytes Internal SRAM. 32 × 8 General Purpose Working Registers. Real Time Counter with Separate Oscillator. Four 8-bit PWM Channels. Four Programmable Serial USART. Controller/Peripheral SPI Serial Interface.
ATmega16U2	Up to 16 MIPS Throughput at 16 MHz. 16k bytes ISP Flash Memory. 512 bytes EEPROM. 512 bytes SRAM. USART with SPI master only mode and hardware flow control (RTS/CTS). Master/Slave SPI Serial Interface
Sleep Modes	Idle. ADC Noise Reduction. Power-save. Power-down. Standby. Extended Standby.
Power	USB Connection. External AC/DC Adapter.
I/O	54 Digital. 16 Analog. 15 PWM Output

Chapter 4

Implementation and Test

Chapter 4: Implementation and Test

4.1 Introduction

The implementation phase of this project marks a pivotal step in realizing the vision of transforming a manual microscope into an automated system equipped with advanced technological functionalities. This chapter delves into the detailed process of integrating automation technologies to enhance the capabilities of traditional microscopy, aiming to revolutionize scientific and medical research practices. By exploring the methodologies, challenges, and outcomes of this implementation, this chapter provides a comprehensive overview of how theoretical concepts are translated into practical advancements in microscopy.

4.2 Block diagram

This section describes the block diagram of components and connections between each component.

Figure 4 1 Block Diagram

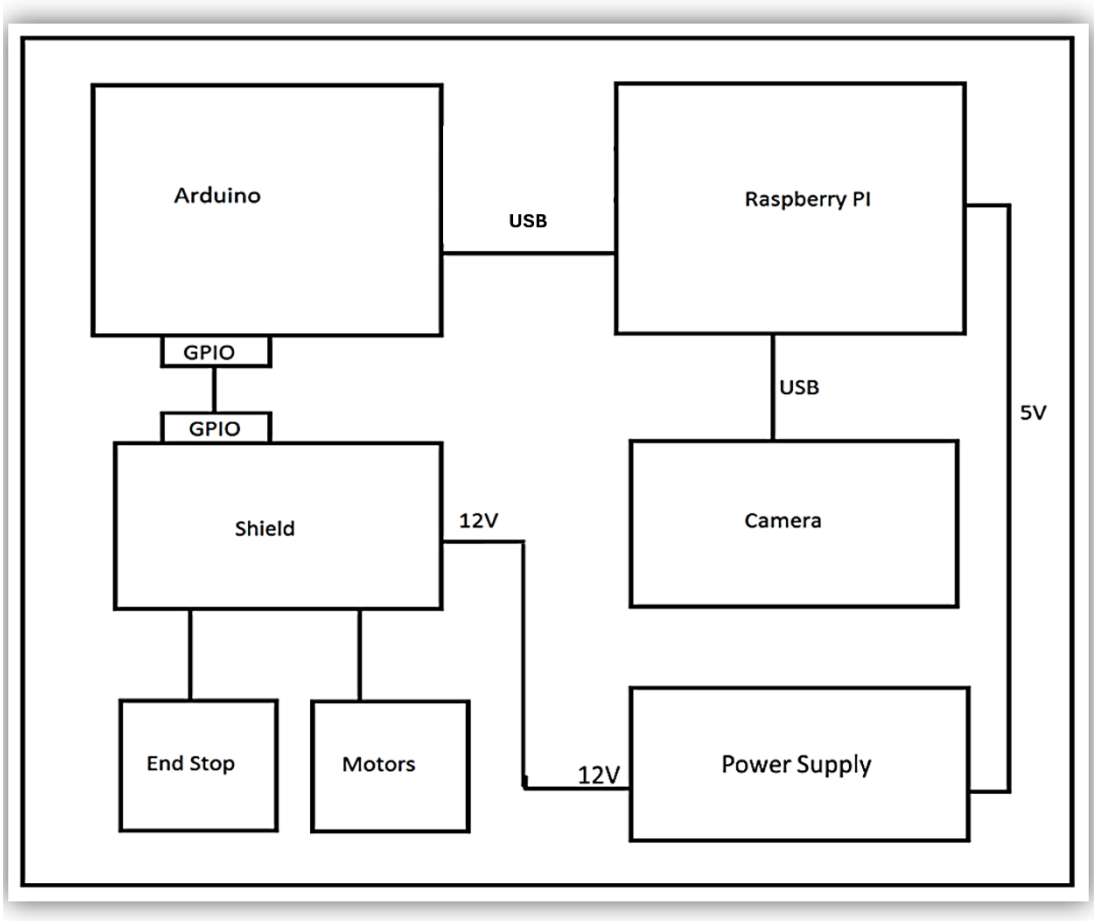


Figure 4 2 Block Diagram with component pictures

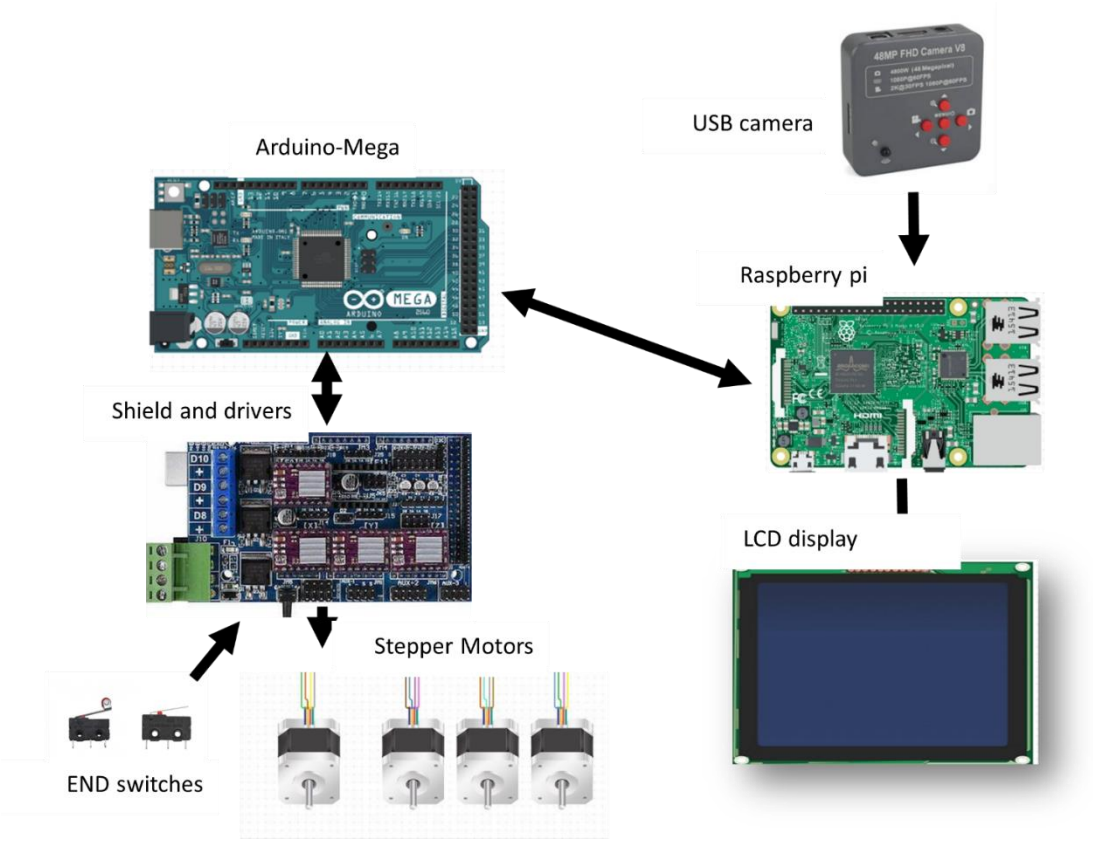


Figure 4 3 Connection wires between camera and Raspberry pi and Sheild

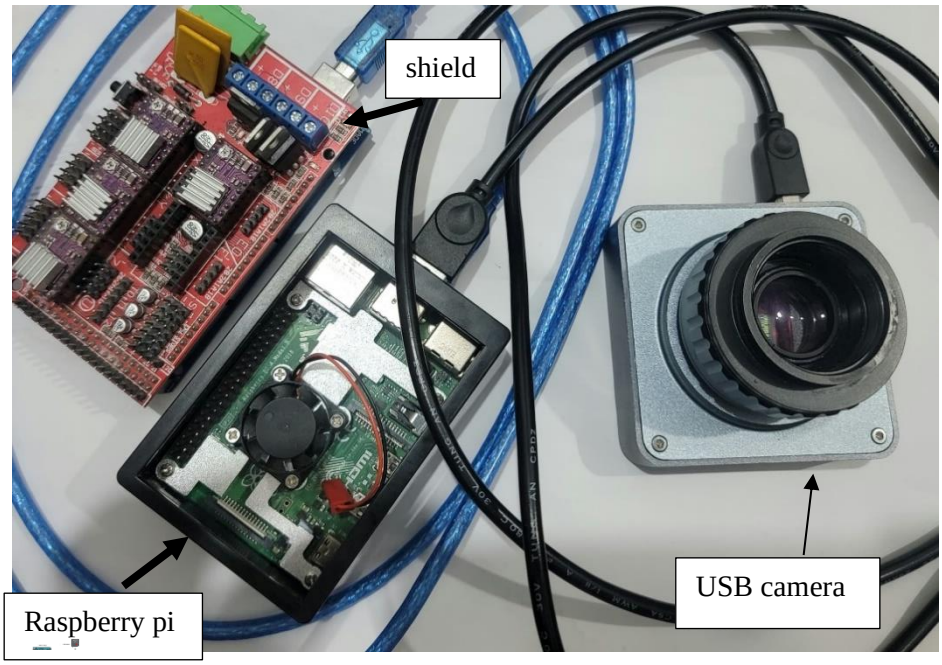
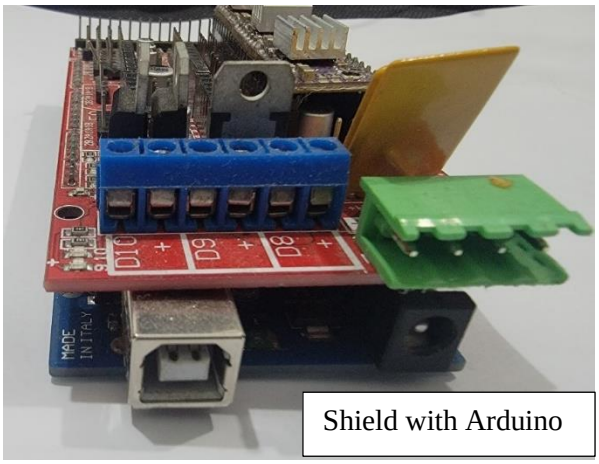


Figure 4 4 Connection between Arduino and RAMPS Sheild



4.3 system architecture:

An automatic microscope system typically divides into two main parts: hardware and software working in tandem. Here's a breakdown of the general architecture:

4.3.1 Hardware Components:

Microscope: The core instrument with lenses for magnification and illumination system for specimen visualization.
Stage: A motorized platform that holds the sample and allows for precise movement in X, Y, and sometimes Z directions.
Camera: A high-resolution camera captures images of the specimen at various magnifications.
Automation System: This may include motors, controllers, and sensors that enable automated control of stage movement, focusing, and illumination.

4.3.2 Software Components:

Acquisition Software: Controls the camera and captures images based on user-defined parameters.
Stage Control Software: Commands the stage motors for precise movement during image acquisition.
Image Processing Software: Analyzes captured images, often using image recognition or machine learning algorithms to identify features of interest.
User Interface: Provides a platform for users to set up experiments, define parameters, monitor progress, and view results.

4.3.3 Inputs:

These are the system's "eyes and ears," providing critical information about the environment and user commands.
• **Camera:** Acts as the system's primary visual input, capturing images or video of the microscope samples as a real-time frame.

• **End Switches:** Function as physical limiters, sending signals when the system reaches its designated boundaries to processing unit.

• **Interface Panels:** Serve as the communication hub, allowing human operators or other systems to send control instructions (orders) to the processing unit.

4.3.4 Outputs:

These represent the system's physical actions, reflecting the decisions made during processing.

• **Motors:** These are the workhorses, responsible for moving the system's various components based on control signals.

• **Interface Display:** Including real-time image display and serial redline for program processing status.

4.3.5 Processing Unit:

This is the brain of the system, where the acquired data is analyzed and decisions are made. The control system utilizes sophisticated algorithms to interpret the visual information from the camera, understand the state of the end switches, and translate user commands from the interface panels into actionable steps.
And this process unit divide into two programming units:

1-Ardiuno:

Arduino considers to be the interconnection between the output units and the main processing unit, It uses the serial ports to receive and process serial signals to send control instructions to the outputs. Control instructions include the following:

- X Axis movements (Right or Left)
- Y Axis movements (Forward or Backward)
- Z Axis movements (Up or Down)
- Objective lenses (4x, 10x, 40x or 100x)

2-Raspberry pi:
It considers to be the main processing unit that receives and processes input signals, and give control instructions into program system to the output components.

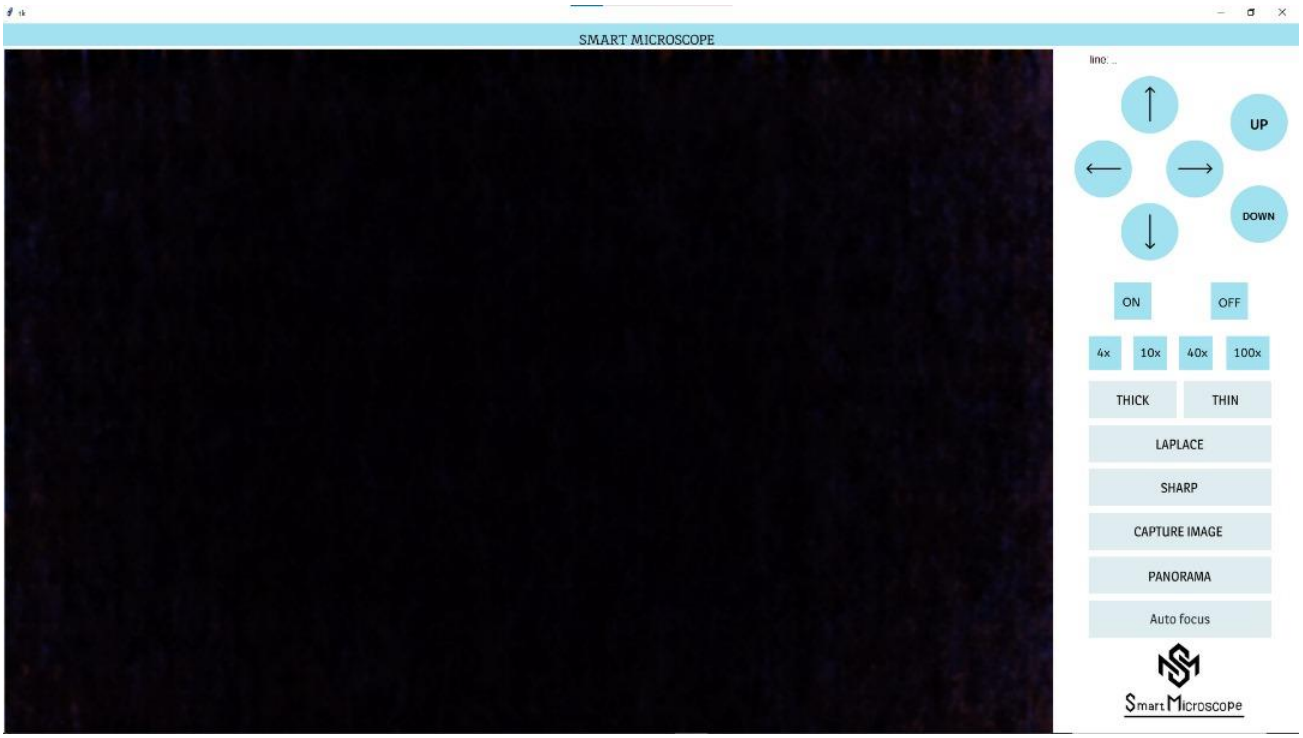
Functionalities:

1-Graphical User Interface (GUI):

As previously mentioned, the Python code creates a user interface for the Raspberry Pi (Figure 1), allowing user interaction for potential features like initiating image capture, adjusting settings, or monitoring the system's status.

The following figure 4.5 showing the interface containing the control panel and the display for the program.

Figure 4 5 Graphical User Interface (GUI)



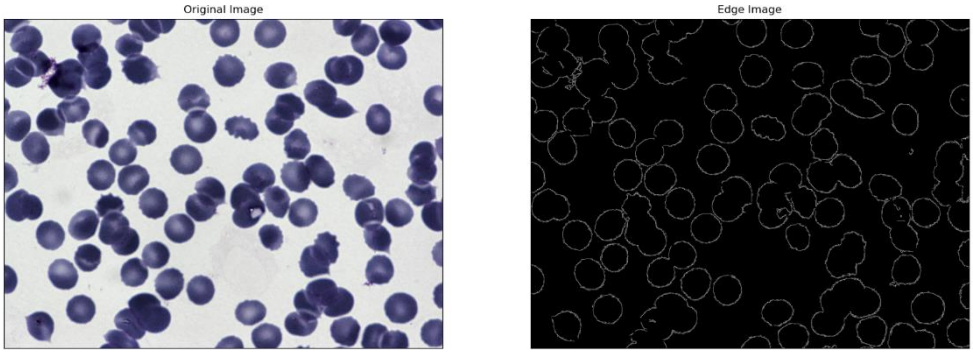
2- Real-Time Image Sharpening using Canny Edge Detection:

The Python code employs image processing algorithms to measure image sharpness. Additionally, it utilizes the Canny edge detection algorithm, a robust technique for identifying and extracting edges in images. The Canny edge detection algorithm involves several steps, including:

- **Noise Reduction:** Applying a Gaussian filter to smooth the image and reduce noise that could affect edge detection.
- **Gradient Calculation:** Calculating the image gradient using Sobel filters to identify areas with significant intensity changes, which are potential edges.
- **Non-Maximum Suppression:** Thinning out the edges by keeping only the pixels with the highest gradient magnitude within a local neighborhood.
- **Hysteresis Thresholding:** Applying two thresholds (high and low) to identify strong and weak edges. Edges with a gradient magnitude exceeding the high threshold are considered strong edges. Those exceeding the low threshold but not reaching the high threshold are only kept if they are connected to strong edges.

Figure 4.6 showing examples of applying canny edges detection.

Figure 4 6 Canny Edge Detection Process



3-Automated Focusing with Multi-Lens Control:

This is a key innovation of the system. The Python code analyzes the Canny edge detection measurements to determine image focus quality. By comparing edge sharpness values, it controls motors responsible for adjusting the lens position. This feedback loop allows the system to achieve optimal focus automatically.

Multi-Lens Support: The system can handle multiple magnification lenses. It starts by analyzing images captured with the lowest magnification lens. Once optimal focus is achieved with this lens, the Python code initiates a lens change mechanism (potentially controlled by motors) and repeats the focusing process with the higher magnification lens. This iterative approach ensures optimal focus for each available lens setting.

4-Panoramic Image Processing:

the system may incorporate functionalities for processing panoramic images, stitching together multiple images captured from different angles to create a wider field of view.

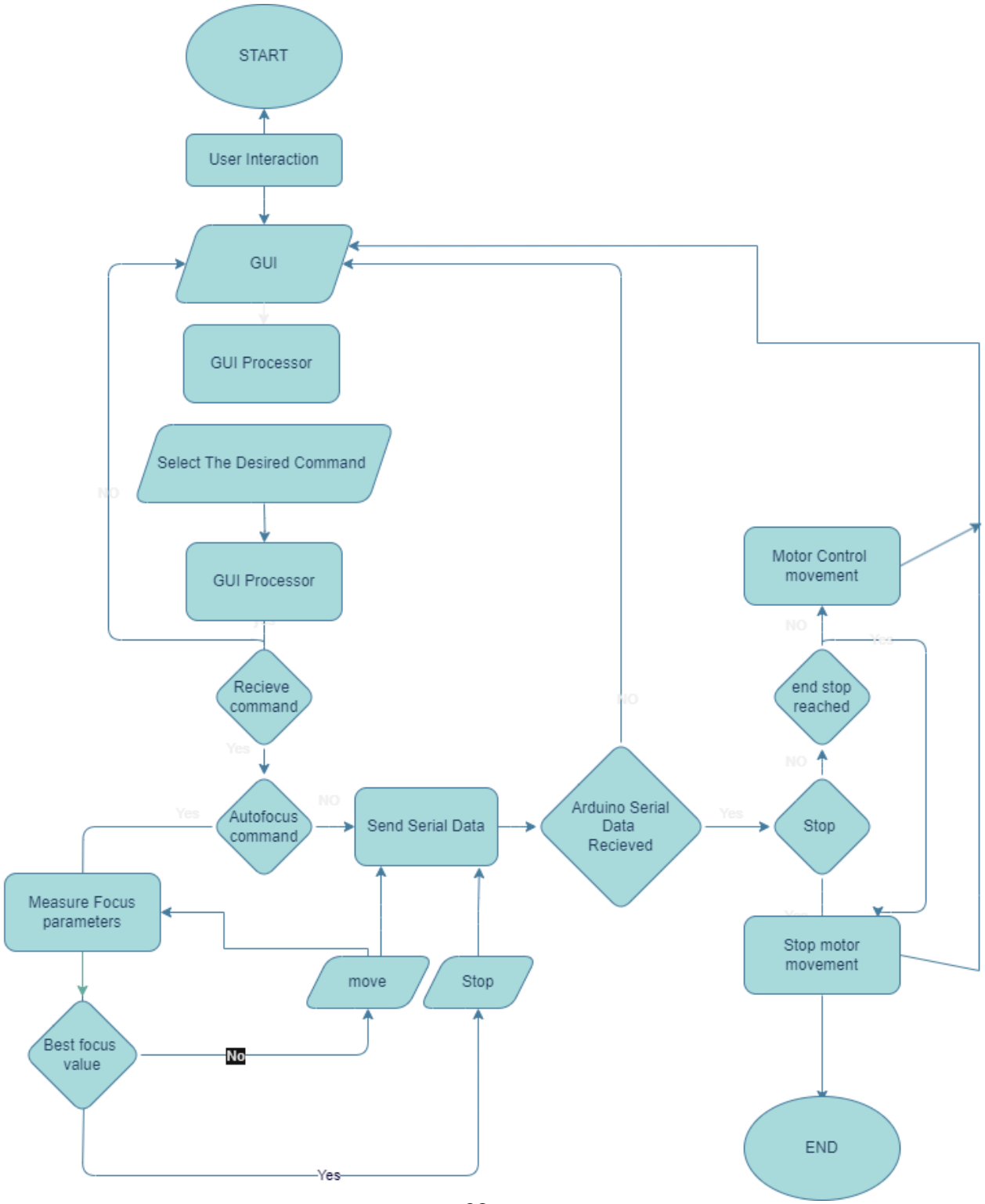
5-Image Capture and Result Visualization:

The system triggers image capture at specific moments (based on focus achievement) or upon user interaction through the UI. The captured images are likely saved for further analysis or display. The Python code may also present the results of image processing, potentially displaying the final focused image or overlays highlighting detected edges.
System also allow user to capture image at any time.

Overall, this system goes beyond basic automated focusing. It utilizes Canny edge detection and motor control to achieve precise focusing with multi-lens support. The optional panoramic image processing capability adds further versatility. This refined system, powered by Python on a Raspberry Pi, offers a compelling solution for applications requiring high-quality, focused images with variable magnification options and wide field of view capabilities.

4.4 FlowChart:

Figure 3 19 Flow Chart



4.5 Malaria Classification Using Deep Learning:

4.4.1 Introduction:

This chapter dives into the critical process of defining and documenting requirements for our final project: a dependable and efficient malaria parasite detection tool. This software system, aimed at aiding doctors and healthcare professionals, aspires to automate malaria diagnosis through cutting-edge deep learning techniques. This phase acts as a bridge between project conception and development. We'll explore various methods and methodologies to gather, analyze, and model the software's requirements. The objective is to ensure the final product seamlessly aligns with the needs of medical personnel and patients combating malaria.

Throughout the following sections, we'll delve into comprehensive requirements analysis and modeling, recognizing them as cornerstones of project success. Topics will encompass the project's overall structure, system lifecycle, diagrams depicting parasite detection workflows, image datasets, and the crucial preprocessing stage. These activities will equip us with a thorough understanding of the program's functional and non-functional requirements, guaranteeing the solution meets high standards in accuracy, reliability, and user-friendliness for malaria diagnosis using microscope samples.

4.4.2 Data Collections:

Building a robust malaria parasite detection tool hinges on the quality and diversity of the data used for training and testing. This project will focus on Plasmodium vivax and Plasmodium falciparum, the two most prevalent malaria parasite species globally, also uninfected malaria data added to classifying normal and the two types of abnormal.

datasets containing microscopic blood smear images serve as a valuable resource for initial training and validation. We will seek datasets specifically containing images categorized as:

- **Uninfected:** Blood smears with no detectable malaria parasites.

  This data set collected from “Kaggle website” released in 2021.

- **Plasmodium vivax:** Blood smears containing the Plasmodium vivax parasite.

  This data collected from “Dataset Ninja” released in 2019.

- **Plasmodium falciparum:** Blood smears containing the Plasmodium falciparum parasite.

  This data collected from “Dataset Ninja” released in 2019.

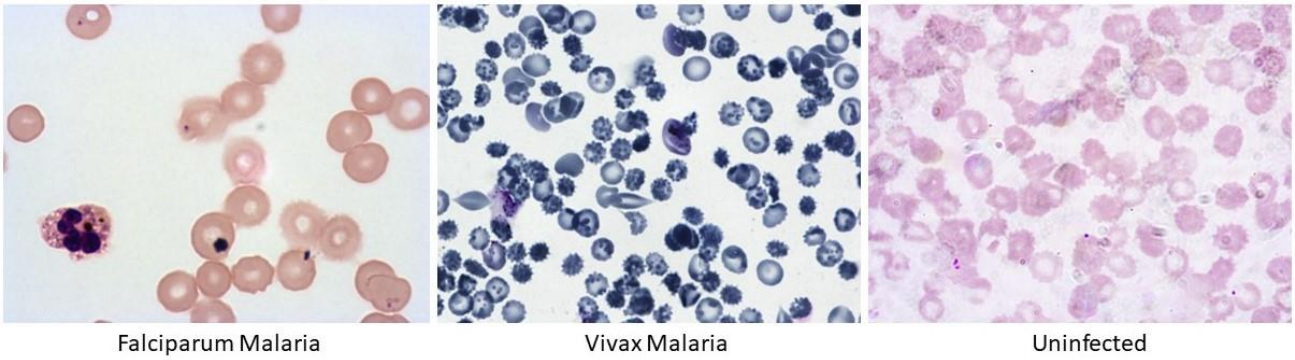
These datasets often encompass a wide range of parasite severities, providing a strong foundation for the model's learning process.

The breakdown of the dataset by class-wise category is presented in the following table 4.1 and the figure 4.7 showing examples of each class samples:

Table 4 1 Dataset Classes with Number of samples for each class

Class	No. of Samples
Uninfected	102
Falciparum	877
Vivax	1161
Total	**2140**

Figure 4 7 Examples of each Class Samples



4.4.3 Block diagram of the general structure of the project analyzing:

The general structure is represented by figure 4.8:

Figure 4 8 general block diagram of project analyzing

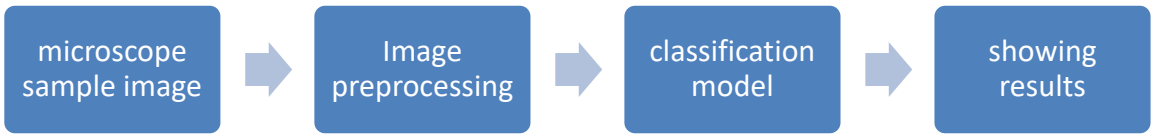
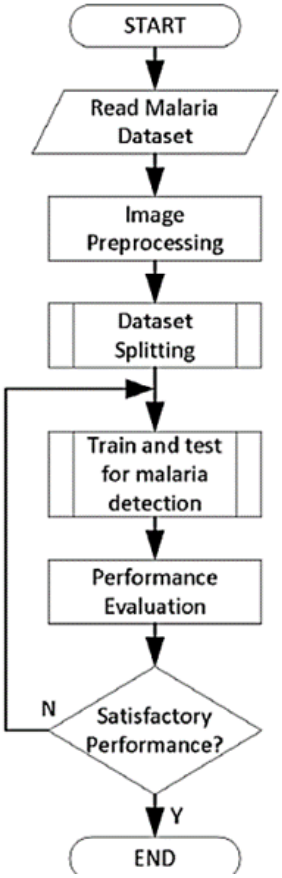


figure 4.9 showing the block diagram of EfficientNetB1:

Figure 4 9 Block Diagram of EfficientNetB1



A block diagram is a visual representation of a system or process. It uses blocks to represent components or stages, and lines/arrows to show connections and information flow between them. Block diagrams are commonly used in engineering and technology fields to simplify complex systems and illustrate their structure and interactions. They provide a clear overview and aid in analyzing system functionality and identifying issues. In Fig 4.8 the first block is where the image is uploaded to the system to be classified, and the second block is for image preprocessing which presents two procedures cropping the image and resizing it, after that classification model is considered as the third stage. Fig 4.9 represents and clarifies the general structure of the project diagram, and finally shows the result is the last block to be given.

4.4.4 Model of malaria classification:

In this section, comprehensive overview of the architecture for the verified model will be provided. The explanation will encompass the entire process, beginning with preprocessing and dataset loading and splitting, and concluding with the model layers.
This model adopts a unique approach to loading and splitting the dataset using Keras from TensorFlow. To streamline the preprocessing process, preprocessing layers within the model architecture have been integrated, eliminating the need for separate preprocessing steps. Additionally, data augmentation techniques have been implemented during training to enhance model robustness. The subsequent sections will provide a detailed explanation of the feature extraction process, encompassing filters and layers employed in this model.

4.4.5 Loading dataset for Normal and the two types of parasitized samples:

In our data pipeline, a specialized function from Keras is utilized, designed explicitly for loading image datasets. By utilizing this function, only image files are loaded, maintaining the integrity and consistency of the dataset. To introduce variability in the dataset and prevent any inherent biases.
Post-shuffling, the dataset is intelligently divided into batches, with each batch containing a specified number of images. Given that the dataset comprises 2140 images, we have carefully chosen a batch size of 32, resulting in a total of 66.857 batches. This particular configuration allows for efficient processing and training, enabling the model to learn from the data in a manageable and optimized manner.

4.4.6 Splitting dataset:

The dataset splitting process was seamlessly integrated within the dataset loading function, aligning with the preconfigured batches. Prior to splitting, shuffling was performed to mitigate any potential biases that may arise during the division process. The dataset was divided according to a predefined ratio, ensuring an optimal distribution for training, validation, and testing. Approximately 85% of the dataset was allocated to the training set, providing a substantial volume of data for model learning. Additionally, approximately 10% of the dataset was assigned to the validation set, enabling effective fine-tuning of hyperparameters and model evaluation. The remaining 5% of images were designated for the test set, allowing for an unbiased assessment of the model's performance. As shown in Table 4.2 This strategic allocation ensures that the model is trained on a substantial portion of the data while preserving separate subsets for validation and testing, ultimately facilitating an accurate evaluation of the model's generalization capabilities.

Table 4 2 Data splitting

Dataset	Split	Number of Images
Train	85%	1819 Images
Validation	10%	211 Images
Test	5%	110 Images

4.4.7 Dataset preprocessing:

The processing steps employed in this model are concise yet effective. To streamline the preprocessing pipeline, specialized layers from Keras have been leveraged, eliminating the need for separate preprocessing steps typically found in other models.

The initial step involves resizing and rescaling the images, both of which are seamlessly integrated within the model architecture. Our approach entails resizing the entire dataset's images to a uniform shape of 240 x 240. This ensures consistency in the dimensions, facilitating compatibility with subsequent layers and computations. Following resizing, there is a rescaling operation by dividing the pixel values by 255. This transformation effectively rescales the pixel intensities within the range of [0, 1]. By normalizing the pixel values, that enhances the model's ability to learn and extract meaningful features, while maintaining numerical stability throughout the training process. By incorporating these preprocessing steps within the training pipeline, the overall workflow will be simplified and optimize the utilization of computational resources. The model seamlessly handles the resizing and rescaling operations, ensuring that the images are appropriately prepared for subsequent layers and training iterations.

4.4.8 Model Layers:

Our CNN architecture is tailored for image classification tasks, leveraging convolutional layers, pooling layers, and fully connected layers. The model aims to achieve high performance by extracting meaningful features and making precise predictions. Various techniques, such as preprocessing, feature extraction, and regularization, are employed to enhance the model's capabilities.
The core of our model comprises multiple convolutional layers. These layers learn and detect visual patterns within the images. By using small filters, the model captures local features and gradually

learns more complex representations.
Pooling layers strategically down sample feature maps, reducing spatial dimensions while preserving important information. This process enhances the model's robustness to image variations and translations, focusing on vital features for classification.
Fully connected layers process extracted features, enabling final predictions. By flattening high-dimensional feature maps into a one-dimensional vector, the model captures abstract representations and learns complex feature interactions.
To combat overfitting, regularization techniques are applied. Dropout layers randomly deactivate neurons during training, encouraging the model to rely on multiple paths and reducing reliance on specific features.
During training, the model is optimized using the Adam optimizer, which dynamically adapts the learning rate. The Sparse Categorical Crossentropy loss function measures the discrepancy between predicted and true labels. Model performance is evaluated using the accuracy metric
Early stopping is implemented to optimize training and prevent overfitting. This technique monitors validation loss and halts training if improvement becomes negligible, ensuring the model's ability to generalize to unseen images.

4.5 Programming languages and libraries:

• **Python:** A high-level, general-purpose programming language known for its readability and extensive libraries. Python is widely used in various domains, including data science, web development, machine learning, and scientific computing.

• **Arduino IDE:** An Integrated Development Environment (IDE) specifically designed for programming Arduino microcontroller boards. The Arduino IDE simplifies the process of writing code, compiling it for the Arduino hardware, and uploading it to the board.

• **Anaconda:** A free and open-source distribution of the Python language that includes a collection of pre-installed scientific computing packages. Anaconda streamlines the installation and management of various Python libraries commonly used for data science and machine learning tasks.

• **Visual Studio:** A powerful, versatile IDE from Microsoft that supports development in a wide range of programming languages, including Python. Visual Studio offers advanced features for code editing, debugging, and project management, making it a popular choice for professional software development.

• **Jupyter Lab:** An interactive web application for creating and running Jupyter Notebooks. Jupyter Notebooks are documents that combine code, visualizations, and explanatory text, making them ideal for data analysis, exploration, and communication. Jupyter Lab provides a user-friendly interface for working with Jupyter Notebooks and offers additional features not found in the classic Jupyter Notebook application.

• **tkinter:** This library provides access to the Tkinter GUI (Graphical User Interface) toolkit in Python. It allows you to create graphical elements like windows, buttons, and menus for user interaction.

• **cv2 (OpenCV):** OpenCV (Open-Source Computer Vision Library) is a powerful library for real-time computer vision and image processing tasks. It offers a wide range of functions for image manipulation, object detection, feature extraction, and more.

• **serial:** This library facilitates serial communication between your Python program and external hardware devices using serial ports. It enables sending and receiving data to and from devices like Arduinos or other microcontroller boards.

• **PIL:** The Python Imaging Library (PIL) provides functionalities for working with image data. It allows you to open, manipulate, resize, and save images in various formats. The ImageTk module specifically helps integrate PIL images into Tkinter applications for GUI display.

• **numpy:** NumPy is a fundamental library for scientific computing in Python. It provides efficient data structures like arrays and matrices, enabling numerical computations and manipulations on large datasets. This library often plays a crucial role in image processing tasks.

• **time:** This built-in Python library offers functions for measuring and manipulating time. It allows you to control delays, measure execution times, and synchronize program execution.

• **threading:** The threading library provides tools for creating and managing threads in Python. This enables concurrent execution of multiple tasks within your program, which can be beneficial for performing image processing while handling user interaction in a GUI or communicating with external devices.

• **pathlib:** The pathlib library offers a convenient way to work with file paths in Python. It provides a class named Path that simplifies path manipulation tasks like checking file existence, constructing paths, and joining directory components.

4. Tensorflow Library:
TensorFlow is an open-source library developed by Google for machine learning and deep learning applications. It offers a comprehensive set of tools and functionalities for building and training machine learning models. TensorFlow supports both traditional machine learning algorithms and deep neural networks, making it widely used in the AI community.

5. Keras Library:
keras is a high-level neural network library written in Python. It provides a userfriendly interface for building and training deep learning models. Keras supports various backends, including TensorFlow, Theano, and CNTK, allowing developers to seamlessly integrate their models with these powerful libraries.

6. Google Colab:
Google Colab is a cloud-based development environment that allows users to write and execute Python code in a web browser. It provides free access to GPU and TPU resources, making it popular for machine learning tasks. Colab offers pre-installed libraries, including TensorFlow and Keras, and supports collaborative work by allowing users to share and collaborate on notebooks. The experiments are performed using a Tesla T4 with 25 GB of RAM.

4.4 Test:

This section delves into the testing and evaluation procedures conducted to assess the performance and functionality of the automated focusing system with multi-lens control. The testing methodology aims to verify if the system achieves its objectives and identifies areas for potential improvement.

4.4.1 Functional Testing:

Verify that the system performs its intended tasks as designed. This involve testing automated focus control with different lenses, image capture functionality under varying focus conditions, and user interface (GUI) operation.

Test Case:

This case verifies Automated Focus Control with Lens Change

1- **Power on** the system and ensure the Raspberry Pi boots successfully.

2- **Launch** the user interface (GUI) on the Raspberry Pi as figure 4.11 showing:

Figure 4 10 Graphical User Interface (GUI)

3- **Select** the desired "Objective lens" options on the GUI shown in figure 4.12:

Figure 4 11 GUI selecting objective lenses

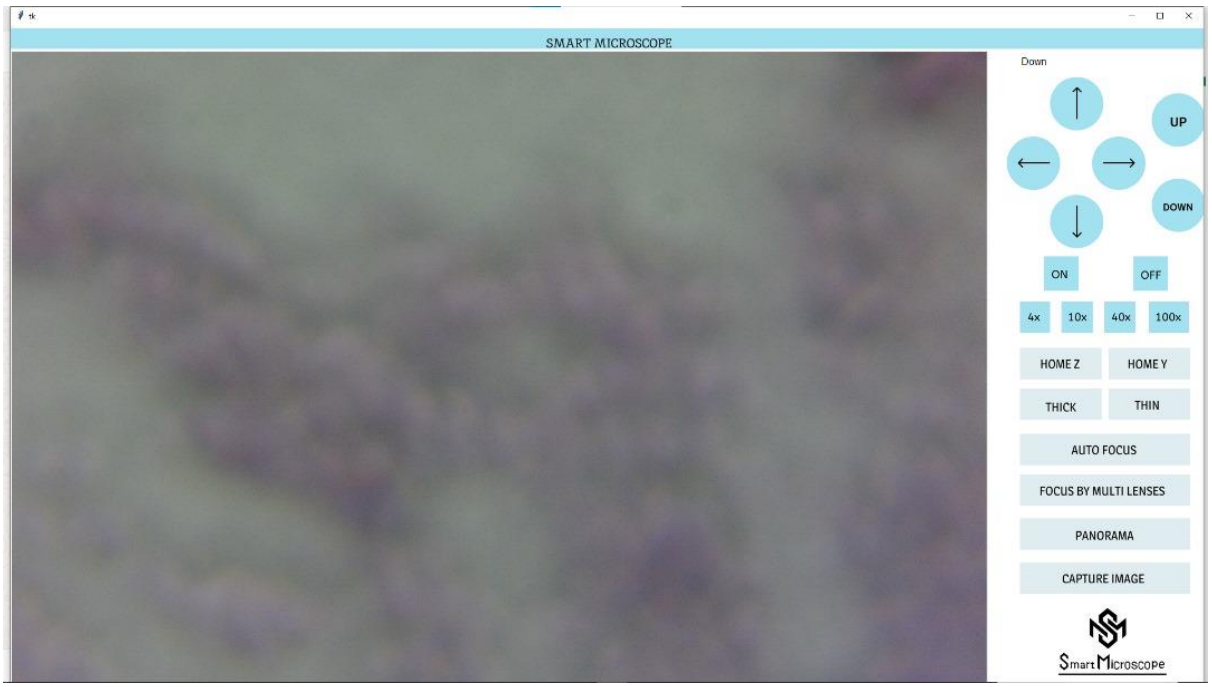
4.4.2 Performance Test:

Evaluate the system's efficiency and effectiveness in achieving optimal focus. This involves measuring focusing speed, accuracy of focus at different magnifications, and image quality under optimal and non-optimal focus conditions.

1-Observe the system's behavior. The system should initiate the focusing process with the selected magnification lens.

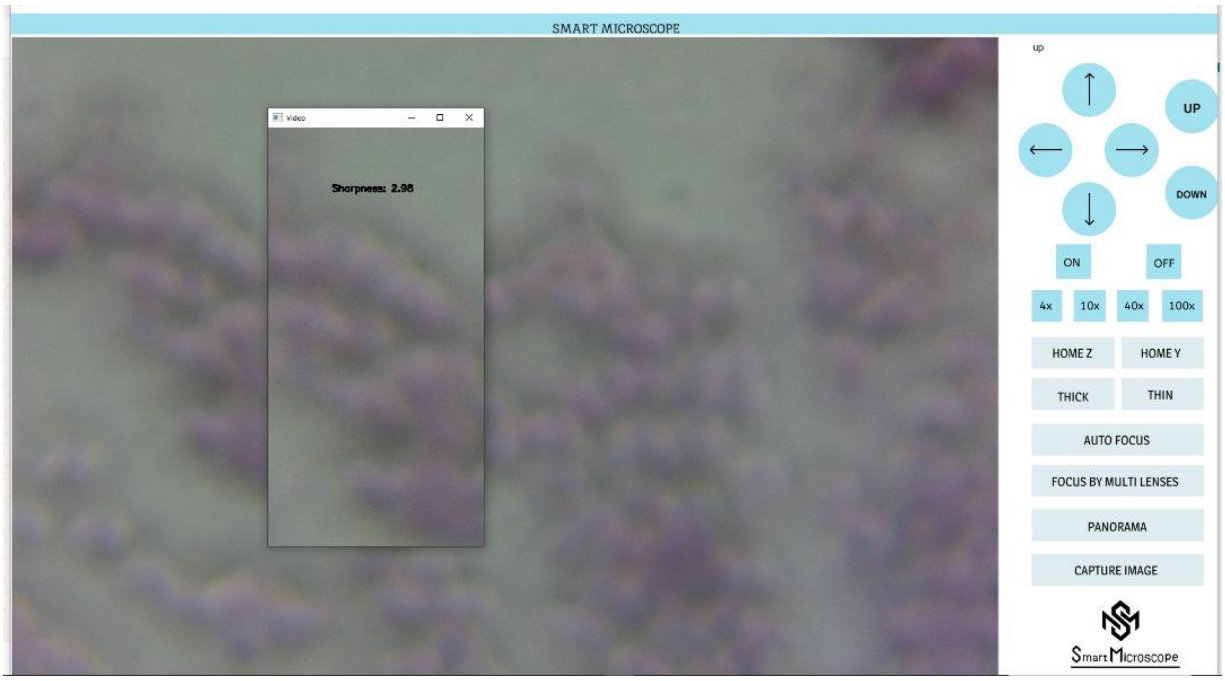
2-Monitor the image preview on the GUI. The image should initially appear blurry or unfocused.

Figure 3 20 Monitoring Process



3-Analyze the Canny edge detection results displayed on the GUI.

Figure 3 21 Measure sharpness



4-Verify that the system automatically adjusts the lens position through motor control.

5-Monitor the image preview on the GUI. The image should gradually become sharper as the system approaches optimal focus.

6-Once the focus is achieved (image appears sharp and Canny edge detection results meet the threshold), the user should be able to capture the image.

7-Verify that the captured image is saved to the designated storage location.

8-change motor status (if necessary)

Expected Result: The system should successfully achieve focus with all lenses, capture images at each optimal focus point, and save them to the designated location.

4.4.3 Robustness Testing:

Assess the system's ability to handle unexpected situations or environmental changes. This involve testing performance under varying lighting conditions, testing error handling in case of motor malfunctions, or testing system behavior with different lens types.

Test Case Description: Evaluate System Behavior Under Different Light Conditions

Test Scenario: The system is typically designed to function under normal lighting conditions. This test case assesses how the system handles different light environments that might impact the focusing process.

Chapter 5

Results and Discussion

Chapter 5: Results and Discussion

5.1 Introduction:

The subsequent chapter delves into a comprehensive analysis of the research findings. It presents a detailed exposition of the results obtained through the employed research methodologies. The discussion that follows provides a critical interpretation of these results, examining their significance within the context of the research objectives and existing knowledge in the field.

5.2 Autofocus Results:

Image Descriptions:

The processed image showcasing enhanced focus and clarity.

Results Analysis:

The autofocus algorithm effectively improved image quality by significantly reducing blurriness. This is evident in the increased sharpness and detail observed in Figures (5.1, 5.2, 5.3) The algorithm demonstrated robustness across various image conditions, consistently enhancing focus without introducing noticeable artifacts.

Figure 5.1 shows Macro image captured with the 4x objective lens:

Figure 5 1 Macro image with 4x

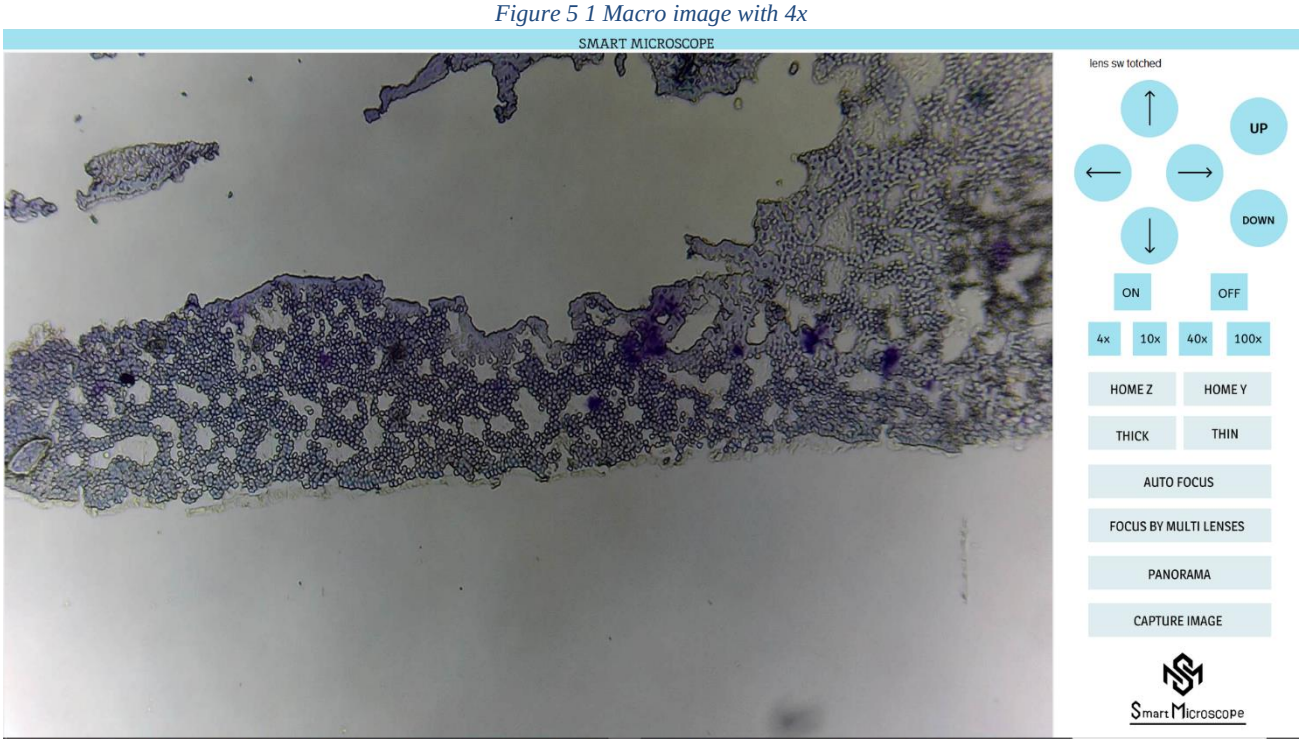


Figure 5.2 shows Macro image captured with the 10x objective lens:

Figure 5 2 Macro image with 10x

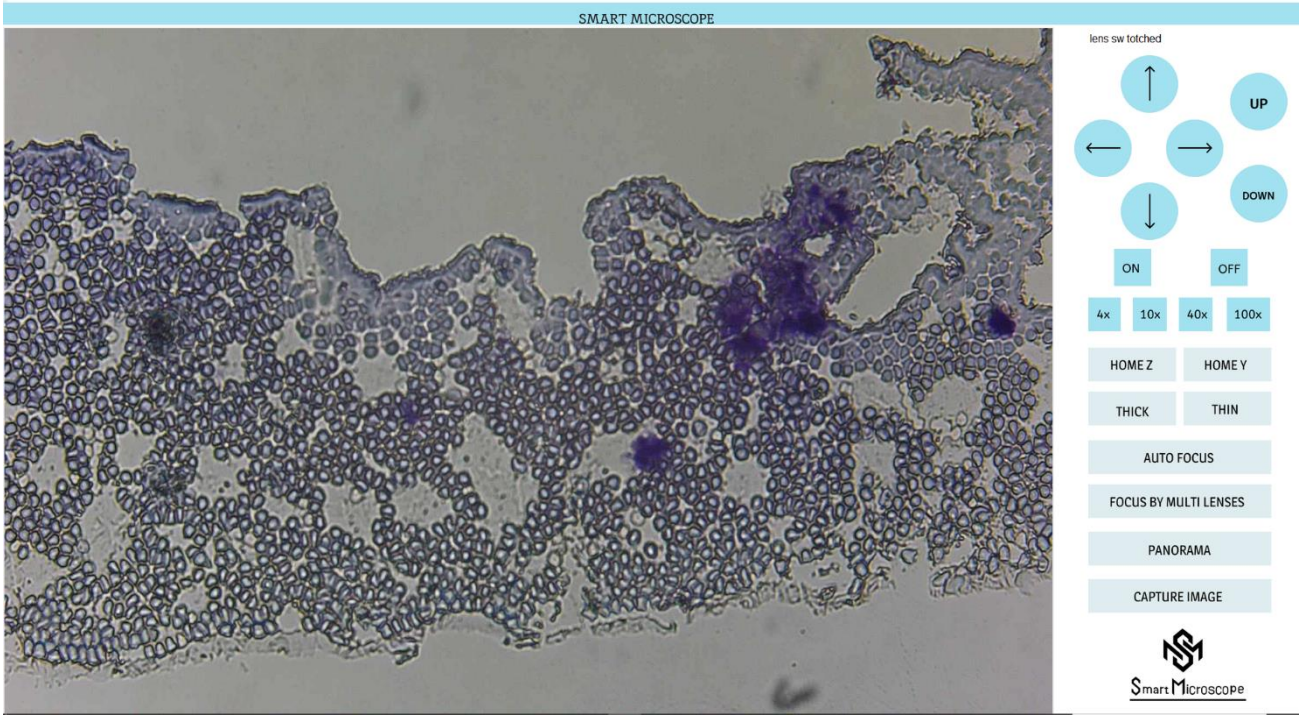
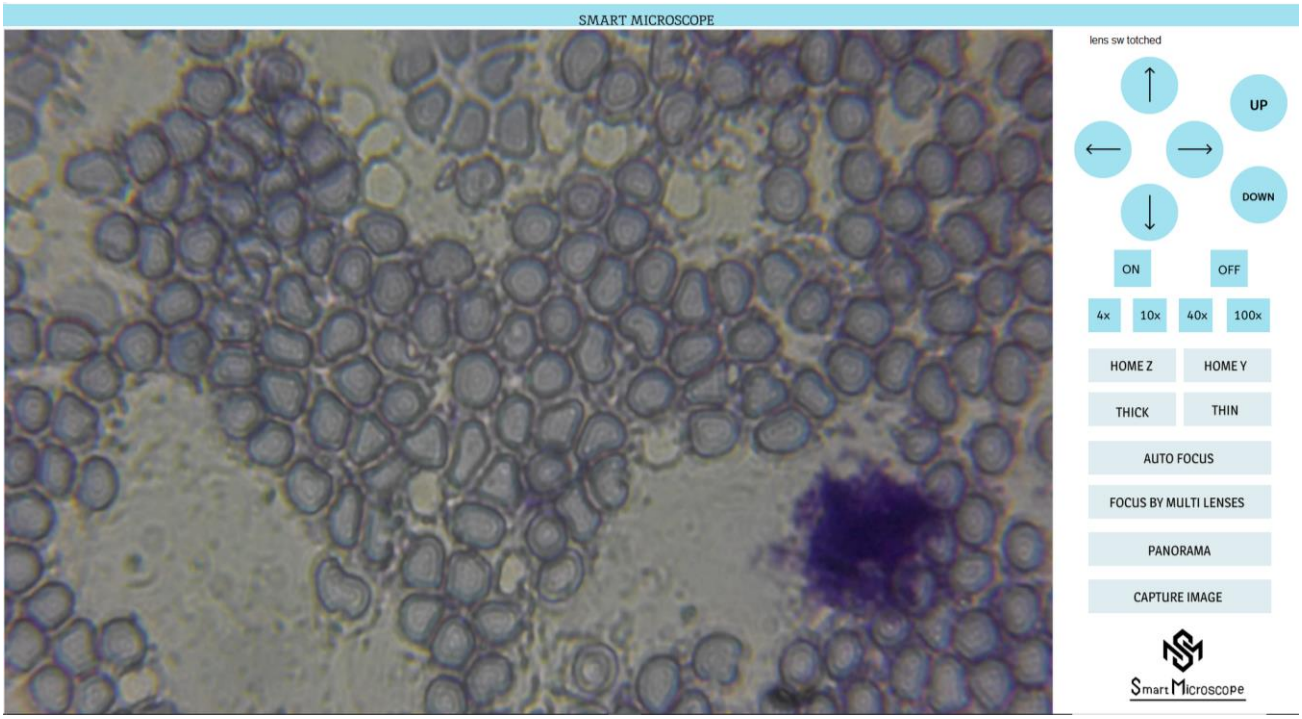


Figure 5.3 shows Macro image captured with the 40x objective lens:

Figure 5 3 Macro image with 40x



5.3 Multi Lenses Focus Results:

The multi-lens approach effectively captured image information across different magnification levels. The 40x objective lens provided the optimal level of detail, as evidenced by the final focused image Figure 5.3. Macro image with 40x. While lower magnification images offer broader context, the 40x image excels in revealing fine structural details crucial for analysis.

5.4 Panorama Results:

Image Descriptions:

Figure 5.4: Overlapping images captured from different viewpoints.
Figure 5.5: The stitched panoramic image.

Results Analysis:
The panorama stitching algorithm effectively combined multiple images to create a seamless panoramic view. The resulting image accurately represents the scene with minimal distortion and color inconsistencies. The algorithm demonstrated robustness in handling various image conditions, producing high-quality panoramas.

5.5 Model Results:

Image Descriptions:

Figure 5.8.4a: A representative blood smear image.
Figure 5.8.4b: Model output highlighting detected malaria parasites with corresponding classifications.
Figure 5.8.4c (if applicable): A zoomed-in view of a detected parasite with species identification.

Results Analysis:

The proposed model demonstrated high accuracy in detecting and classifying malaria parasites within blood smear images. The model successfully differentiated between infected and uninfected samples, as well as accurately identified parasite species (P. falciparum and P. vivax). These results highlight the model's potential as a valuable diagnostic tool for malaria.

This section provides a comprehensive discussion of the evaluation measures employed to assess the performance of the proposed methods for the model that is used in this project. Additionally, it covers the system and software requirements necessary for the three models' training and evaluation. Detailed information regarding the various hyper-parameters and their corresponding values is also provided. Furthermore, a thorough analysis of the results obtained through the proposed method is presented in this chapter.

Evaluation Measurements:
Evaluation measures are quantitative metrics that are used to evaluate the performance of a deep learning model. They are used to compare the performance of different models or algorithms on a particular task, assess the effectiveness of a model or algorithm in solving a particular problem, and identify areas for improvement. The valuation measures that are being used in this research work are accuracy, F1-Score, precision, recall/sensitivity, and confusion matrix.

Accuracy: It is calculated by dividing the number of correct predictions by the total number of predictions and can be expressed by Following Eq.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Equ. 5 1

where, TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative respectively.

Precision: Precision measures the fraction of instances predicted by the model as belonging to a specific class that belongs to that class, and is calculated by Following Eq.

$$\text{Precision} = TP / TP + FP$$

Eq. 5 2

Where:

- TP (True Positives): Number of instances correctly predicted to belong to the class.
- FP (False Positives): Number of instances incorrectly predicted to belong to the class.

Recall: Recall measures the fraction of instances that actually belong to a specific class that were correctly predicted by the model, and is calculated by Following Eq.

$$\text{recall} = (TP / (TP + FN))$$

Eq. 5 3

Where TP and FP previously mentioned.

F1-score: The F1-score is a harmonic mean between precision and recall, aiming to provide a balanced view of both metrics. It's calculated by Following Eq.

$$\text{F1-score} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$$

Eq. 5 4

Support: Support is the total number of instances in a particular class.

Confusion matrix: A confusion matrix is a summarized form of predicted results that helps to measure different evaluation measures like accuracy, recall, precision, etc. It summarizes the overall performance of the model by breaking down the number of correct and incorrect predictions for each class. Also, A confusion matrix is used to assess how well a classification model is generalizing on unseen test data. For each class, the confusion matrix highlights the number of the predicted labels in the horizontal x-axis with its true label in the vertical y-axis. This is done by first comparing labels obtained from the model prediction with the true labels and then counting the number of times the correct combination of predicted and true value occurs.

Analyze Results:

In this model, a deep learning approach is proposed for the classification of Malaria parasite using pre-trained efficientNetB1 on Malaria sample images. The dataset without augmentation consists of 102 for Uninfected samples and 877 for falciparum samples and 1161 for vivax samples. All the images were going through the preprocessing phase and obtained 99.68% test accuracy and 100% training accuracy more details are shown in Table 5.1 results of fine-tuned. Moreover, the curves of model accuracy and loss functions can be seen in Fig 5.5. model accuracy and loss curves. As noticed, this model of EfficientNetb1 gets stable rapidly from likely epoch 12 compared to the CNN models used, and that’s probably to the complex architecture of EfficientNet family in general. A confusion matrix is used to assess how well a classification model is generalizing on unseen test data. For each class, the confusion matrix highlights the number of the predicted labels in the horizontal x-axis with its true label in the vertical y-axis. This is done by first comparing labels obtained from the model prediction with the true labels and then counting the number of times the correct combination of predicted and true value occurs. The performance of the proposed technique in terms of the confusion matrix is shown in Fig 5.4. model confusion matrix. Fig 5.10. is The GradCAM visualization of different classes.

Table 5 1 Classification Report

-	PRECISION	RECALL	F1-SCORE	SUPPORT
Falciparum	**0.99**	**1.00**	**1.00**	**132**
Vivax	**1.00**	**0.99**	**1.00**	**174**
No-Malaria	**1.00**	**1.00**	**1.00**	**15**
Accuracy	**1.00**			**321**
Marco Avg	**1.00**	**1.00**	**1.00**	**321**
Weighted Avg	**1.00**	**1.00**	**1.00**	**321**

Figure 5 4 Model Confusion Matrix

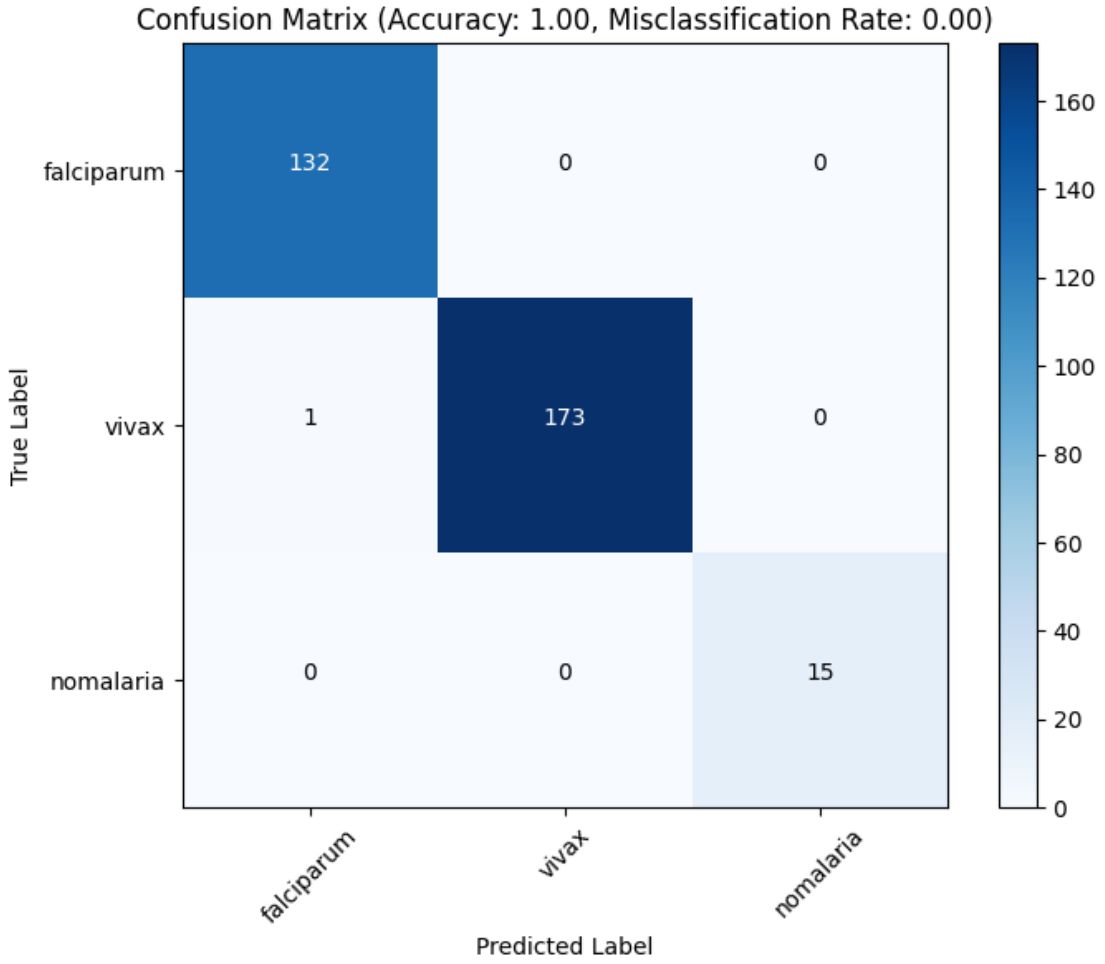


Figure 5 6 model accuracy and loss curves

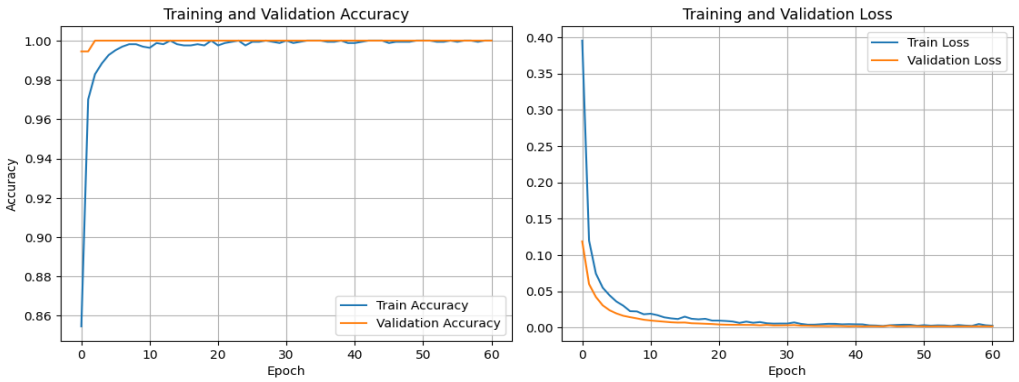
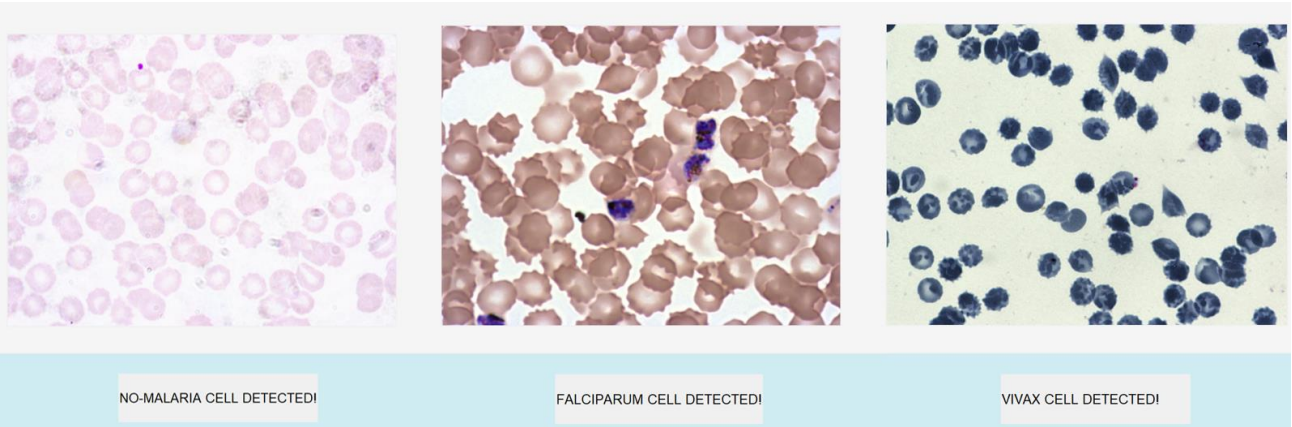


Figure 5 5 The GradCAM visualization of different classes



Chapter 5

Conclusions and Recommendations

Chapter 6: Conclusions and Recommendations

6.1 Conclusion:

The successful development and implementation of an automated microscopy system represents a significant advancement in the field of biomedical imaging. By integrating advanced hardware components, image processing techniques, and deep learning algorithms, this research has demonstrated the feasibility of converting a manual microscope into a high-throughput, accurate, and autonomous platform.

The system's ability to automate image acquisition, including stage movement, focus adjustment, and image stitching, significantly enhances efficiency and reduces human error. Moreover, the integration of deep learning algorithms has resulted in exceptional performance in malaria parasite classification, achieving 100% accuracy in training data. This breakthrough holds immense potential for revolutionizing malaria diagnosis and treatment, enabling rapid and precise identification of infected blood cells.

While the results presented in this study are promising, further research is necessary to evaluate the system's performance on a larger and more diverse dataset. Additionally, exploring the integration of other deep learning architectures and techniques could potentially improve classification accuracy and robustness. Ultimately, this automated microscopy platform has the potential to transform various fields of scientific research by providing researchers with a powerful tool for efficient data acquisition, analysis, and interpretation.

6.2 Recommendations:

1. Server and Microscope Integration
A robust server infrastructure will be developed to seamlessly connect Raspberry Pi-equipped microscopes with high-performance analysis computers. This integration will facilitate efficient data transfer, remote access, and collaboration. Prioritizing data security, cloud-based solutions will be explored alongside edge computing for real-time analysis. To optimize data transmission, machine learning-based image compression techniques will be investigated.

2. GPU-Accelerated Panorama System
To significantly improve image stitching speed and efficiency, the panorama system will be optimized for GPU acceleration. By leveraging the parallel processing capabilities of GPUs, we aim to achieve real-time stitching for large-scale image datasets. This optimization will involve adapting existing algorithms to the GPU architecture and exploring GPU-specific libraries for efficient implementation.

3. Intelligent Light Source Control
An adaptive light source system will be developed to automatically adjust lighting conditions based on sample characteristics. Advanced sensors will be integrated to accurately characterize samples, and machine learning algorithms will be employed to generate optimal lighting profiles. User-defined presets will also be included for specific applications.

4. Enhanced Malaria Classification

The malaria classification system will be refined to accurately identify parasite species (Plasmodium falciparum and Plasmodium vivax) and their life cycle stages. Deep learning models will be implemented to improve classification accuracy and robustness. A modular system will be designed to accommodate future expansion to other diseases. Rigorous quality control measures will be established to ensure reliable results.

5. Multi-Disease Analysis Platform

The analysis platform will be extended beyond malaria to encompass a broader range of diseases. A flexible framework will be developed to accommodate diverse disease-specific algorithms. Integration with electronic health records will be prioritized for seamless data management. Diseases with significant global impact and limited diagnostic tools will be given priority for development.

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