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ENGINEERING SCIENCE

PRAXIS III

DESIGN PROPOSAL — AUTOMATED MICROSCOPIC MALARIAL DIAGNOSIS

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Contents

1 Executive Summary

E-Health Africa (eHA) provides clinical lab malarial tests. However, it struggles to keep up with the need for accurate malarial tests as it is based in an endemic country—Nigeria. The diagnostic process is slow as it involves five independent tests, it requires skilled lab technicians, and it is prone to human error. eHA requires a streamlined solution for testing malaria in their labs. There is a bottleneck in an "impedance mismatch" between skilled workers available and the timeline of a testing epoch. The goal of this proposal is to design a solution to improve the efficiency and accuracy of malaria diagnoses for eHA and other less economically developed endemic countries.

Our team believes that automating the different tests such as hematology analyzing, microscopy, and RDTs will lessen the need for highly trained clinical technicians, increase efficiency, and improve the accuracy of diagnoses. In addition, by automating the analysis, eHA can utilize a larger subgroup of their staff to process patient samples, as the staff would not need the training and experience to accurately identify malaria.

Due to time constraints, the focus of this proposal will be scoped down to a single manual diagnostic test: the microscopy test. Microscopy malaria tests are the most standard type of testing for endemic countries and the false negatives can typically be attributed to human error. Our team of highly qualified engineers, specializing in machine intelligence, believe that implementing machine intelligence will alleviate many of the accuracy and bottleneck constraints of malaria diagnoses in endemic areas.

2 Opportunity Statement

2.1 Situation

According to the opportunity statement, eHA's mission is "to build stronger health systems through the design and implementation of data-driven solutions that respond to local needs and provide underserved communities with the tools to lead healthier lives" [8]. To test for malaria, rapid diagnostic testing (RDT) is used which requires different machines for different parameters, each of which takes a different amount of time to make a diagnosis. The five machines include a microscope, hematology analyzer, chemistry analyzer, urinalysis machine, and blood glucose meter, all of which are used simultaneously. The only machine that is automated is the urinalysis machine; the rest are used by lab technicians.

Research Project Manager at eHA, Tolulope Oginni, commented on some of the issues associated with malaria diagnoses at eHA [8]:

- RDT produces faint lines that are hard to read and prone to human error
- Malaria microscopy tests require highly trained staff; however, interpretations can be subjective and are prone to human error
- Diagnostic accuracy is of utmost importance, particularly for children under the age of five and pregnant women
- eHA would like to automate tests such as the RDT and microscopy test

An interactive version of this document can be found here

2.2 Analysis of Situation

According to the synopsis and additional information provided by Tolulope, eHA requires a streamlined solution for testing malaria in their labs and that the bottleneck lies in an "impedance mismatch" between skilled workers available and the timeline of a testing epoch.

Our primary stakeholder, eHA, requires data-driven, automated test processing for their manual machines which could increase their overall throughput of tests [9].

In a study from Equatorial Guinea, it was found that microscopy and RDT malaria diagnosis had a 19.4% and 13.3% false-negative rate [1]. This indicates that it may be difficult to give an accurate microscopy malaria diagnosis. However, the study also commented on the lower accuracy of lab technicians from the Continental Region, suggesting that lack of training may be the cause for high false-negative rates. Furthermore, a study in Kenya found "the diagnostic accuracy of malaria microscopy was positively associated with refresher training in microscopy." This information in combination with microscopy already being the "gold standard" for malaria diagnosis in endemic countries (due to its high sensitivity of 50-500 parasites/μL, its inexpensive procedure, and allowing for the diagnosis of species and density of parasites) guides us to believe that improving the microscopy diagnosis will be the most beneficial to eHA and other endemic regions [1].

2.3 Preliminary Scope

The scope of this project will be narrowed down to automating the malaria microscopy testing as its false negatives are largely attributed to lack of training, most endemic malaria testing centers already use microscopy diagnosis, and it requires skilled technicians which can bottleneck the throughput of diagnostic results.

2.4 Stakeholders

- The primary stakeholder is e-Health Africa (including the Research Project Manager Tolulope Oginni and the lab technicians)
- The Nigerian patients requiring testing for malaria
- The equipment manufacturers
- The University of Toronto (including our team and the FaCT) and Georgia State University

2.5 Value Proposition

Malaria has been identified as one of the most serious health issues today [6]. It has a substantial and steady burden on Nigeria and other less economically developed endemic regions of tropical Africa. Clinics like eHA host the necessary resources to fight a fraction of an international issue that infects 300 million people per year, and greatly impacts the lives of many more [6].

Epidemics have numerous negative impacts, including forcing caretakers to take a leave from work, social distancing, and closed schools and other public services, all of which take a toll on the society and economy [14]. Vulnerable populations suffer disproportionately because they have limited access to healthcare and financial support. The United Nations has identified a sustainability goal for everyone to have good health and well-being. This goal aims to "ensure healthy lives and promote well-being for all" [15, 13].

By enabling faster, more accurate, diagnoses at eHA and similar service environments, clinics will increase their throughput, spend more effort on providing treatments and diagnosing difficult cases,

administer treatments faster, and spend more resources on treating more vulnerable populations. Furthermore, by improving local health, Nigerian citizens would benefit from reduced limitations on time, monetary, and education restraints.

To align with eHA's mission, we converged on the following regarding the objectives of our design:

2.6 High-Level Objective (HO):

To provide an automated data-driven solution to replace the microscopy step in malaria diagnosis. Specifically, we aim to design a deep learning-based approach in identifying and classifying the malaria cells in the input images.

2.7 Low-Level Objectives (LO):

The design would have to be available to eHA and staff in other less economically developed endemic countries without requiring external resources to ensure the solution works, so it will be designed for affordability, assembly, testability, and maintainability.

The solution should be usable by all staff members, so it will be designed for usability and safety.

Lastly, the solution must meet the standards of a trained technician, so it will be designed for efficiency, accuracy, precision, transparency, and interpretability.

By following the low-level objectives laid out, the design will be available, usable, and produce results at least as reliable as technicians.

3 Team

As an Engineering Design student team, we value empathy, efficiency, sustainability, and improving the quality of life when we tackle any problems. We are fully aware of the importance of empathy in the engineering design process and therefore make empathy our first priority team value. Our value for empathy allows us to better understand the stakeholders' situation and thus lets us create a better design. In addition, we want to make sure that our design is sustainable for the stakeholders and can be used for a long period of time without the need for replacement or redesign. Furthermore, we want our final design to have an impact on not only our directly-impact stakeholders, but also have an impact on those who will benefit from our technology in the future.

Project Manager: Amy Saranchuk
Responsibilities: Oversee and manage project operations, facilitate meetings, keep track of progress and dependencies, present on progress
Qualifications: Amy is majoring in Machine Intelligence at the University of Toronto and has had multiple experiences with engineering design projects. These experiences will allow Amy to guide a highly skilled engineering team to achieve the high-level objectives set out in this proposal.

Assistant Project Manager: Emily Traynor
Responsibilities: Assisting in project management activities such as note-taking, planning and facilitating meetings with stakeholders as well as researching to support executive decisions
Qualifications: Emily is majoring in Machine Intelligence and minoring in Business allowing her to appropriately plan and understand technical deliverables, but also effectively communicate technical information with stakeholders. She also has professional experience in consulting, engineering design, and research, allowing her to support writing and researching efforts.

Procurement Lead: Charles Li
Responsibilities: Risk coordinating, issues coordinating, and cost coordinating
Qualifications: Charles is majoring in Math, Statistics and Finance, and minoring in AI. Charles has a background in business finances making him the ideal candidate to manage costs, risks and all financial aspects of the project. He also has experience writing engineering reports and is very detail-oriented, ensuring that all details are captured in deliverables.

Technical Expert/Design Engineer: Nishkrit Desai
Responsibilities: Manages the study, research, and development of ideas, and collaborates with the software and management team to implement designs
Qualifications: Nishkrit has vast experience in machine learning, research and prototyping. He currently does Deep learning and Robotics research at the Vector Institute. These experiences make Nishkrit more than qualified to guide the design and implementation process.

Software Engineering Lead: George Saad
Responsibilities: Software implementation, collaborating with **design engineer/technical expert**, and managing technical deliverables
Qualifications: George's past experience in software development through industry internships, freelance projects, and open source contributions has made him a key asset in our team. His background working on large software projects gives him the technical expertise to succeed in this role.

4 Background

4.1 Primary Stakeholders

- The primary stakeholder is e-Health Africa including the Research Project Manager Tolulope Oginni and the lab technicians. This tool will help the lab technicians by speeding up the technical aspect of their job, letting them analyze more malaria tests in a shorter amount of time. eHA may require staffing changes to accommodate the new machinery and may need to re-train the lab technicians. The overall procedure for diagnosing malaria will also be slightly different.

4.2 Secondary Stakeholders

- One secondary stakeholder is the Nigerian patients requiring testing for malaria. An automated microscope would allow malaria testing to be faster, giving patients their results quicker. Automated machinery also reduces human error, reducing the likelihood of a false positive or false negative result. This directly aligns with the UN sustainability goal for good health and well-being, which aims to "ensure healthy lives and promote well-being for all" [15].
- Another secondary stakeholder is the equipment manufacturers, whose job will be directly impacted by the new proposed microscope design. They may require new machinery and training to produce the new design.
- The final secondary stakeholder is the University of Toronto (including our team and the FaCT) since they are the organizers of this project, and Georgia State University since their role in the project will be affected by the chosen design.

4.3 Scope

Using Functional Decomposition, we broke down the problem into its key components: the five machines used to diagnose malaria. From this, we scoped it down further to the microscope and broke this down into preparing the slides and analyzing the slides. We chose to move forward with the slide analysis and broke it down further into a hardware or software approach. We decided on a software (specifically machine intelligence) approach. Thus, after scoping down the situation we are focusing on automating the process of determining whether a blood sample has malaria from the microscope using machine intelligence.

4.4 Service Environment

The design we are proposing must be usable in a lab environment, specifically in the e-Health Africa lab. The machinery must also be manufacturable in a standard factory.

4.5 Previous Approaches

4.5.1 Single Cell Classification

A research study by Rajaraman et al. showed that using a CNN based deep learning model on segmented cells (single cells from a blood sample) resulted in 98.6% accuracy in malaria detection, which is the current state-of-the-art [11]. This approach, however, only performs classification on single well-segmented cells that have been carefully curated by-hand.

4.5.2 Whole Slide Bounding Box

There have also been a couple of other approaches that aim to draw boxes around the parasites in an image of a slide sample [4]. These methods do not have statistically robust solutions for handling a large variation of slide samples. They do offer a transparent solution that could potentially improve the efficiency of the diagnosis process, however, these methods to not assist with the classification of the parasitized cells. From our research, this seems to be the bottleneck in the entire process as the lack of training as well as the tedious nature of the task reduce the reliability of the results while slowing down the diagnosis.

4.5.3 Hardware for Automating Microscopic Diagnosis

We also found several projects that have provided hardware for automating microscopic imaging [7]. These projects aimed to provide an "imaging plugin" for microscopes so that the existing machinery could be easily integrated with the software that automates the diagnosis process. These hardware solutions are, however, powered by rather primitive algorithms that do not provide informative results that accelerate the diagnosis without making compromises on the reliability of the results. The main improvements we can offer here are on the side of statistically robust results by providing even-more-robust deep-learning models. We aim to provide a solution that gives the best of what previous approaches have to offer, while structuring our design such that its flaws are easily surfaced. This would allow lab technicians to benefit from the efficiency gains our solutions provides, while being able to manually intervene and quickly resolve the issue when our system does not meet the required standards.

4.6 Requirements

After careful consideration of each stakeholders' needs, we have converged on **six high-priority objectives: accuracy, precision, usability, efficiency, safety, and interpretability**. The technicians

require proper safety, the ability to interpret the data produced by our design, and a machine that is easy to use with minimal training; the patients require accurate, precise, and efficient results. **The low-priority objectives are transparency, affordability, assembly, maintainability, and testability**. The equipment manufacturers require the machine to be easily assembled; both the equipment manufacturers and e-Health Africa require the design to need as little maintenance as possible; our team requires the data produced to be transparent and the design to be easily testable. To validate our design, it will be tested with a set of sample data.

5 Design Considerations

The following table breaks down the higher priority requirements that will be the focus of the design cycle, as well as lower priority requirements that will be optimized when possible.

5.1 Higher Priority Requirements (HPR)

Objectives: Accuracy (HPR1)
Metrics: Percentage of false negatives and total percentage of correctly diagnosed samples **Constraint:** False negative rate must be less than 19.4% (a false negative rate from a similar service environment) [1]. The overall accuracy of conclusive results should be at least 80% to be comparable of technician accuracy [2]. **Criteria:** Less false negatives is better and higher accuracy is better

Objectives: Precision/Uncertainty (HPR2)
Metrics: The distribution of results which is conveyed in the confidence interval **Constraint:** The confidence intervals should at least bound at least 80% of the results **Criteria:** The higher the precision, the better

Objectives: Usability (HPR3)
Metrics: Level of training required to follow instructions correctly **Constraint:** Must be usable by at least the lab technicians without additional training **Criteria:** The less training required to follow the better

Objectives: Efficiency (HPR4)
Metrics: Time taken to test per slide sample. Measured as wall-clock-time **Constraint:** Must be at least as efficient as the original processing pipeline **Criteria:** The more efficient the better

Objectives: Safety (HPR5)
Metrics: The number of hazards associated with the machine **Constraint:** Follow safety standard from the "ANNEX I – General safety and performance requirements" [16] **Criteria:** The fewer hazards associated with the machine the better

Objectives: Interpretability of Results (HPR6)
Metrics: The number of output variables that can easily be traced back to a supplied input, i.e. how easy is it to interpret the why the results look as such **Constraint:** The result must be understood by regular technicians **Criteria:** The easier to interpret the output, the better

5.2 Lower Priority Requirements (LPR)

Objectives: Affordability (LPR1)

Metrics: Cost of materials and manufacturing
Constraint: Less than $150 CAD
Criteria: Lower cost is preferred

Objectives: Transparency of Model (LPR2)

Metrics: How well lab technicians can draw a cause/effect relationship to avoid the solution being a black-box, which can be measured by using feedback surveys
Constraint: The solution must indicate at least the most significant factor in concluding a result
Criteria: The easier to draw a cause and effect relationship between data and results, the better

Objectives: Maintainability (LPR3)

Metrics: How often the machine requires external maintenance
Constraint: The design should not require external maintenance once setup
Criteria: The less maintenance required the better

Objectives: Assembly (LPR4)

Metrics: How many resources are required to assemble the design
Constraint: Existing staff members should be able to assemble the design
Criteria: The less resources required the better

Objectives: Testability (LPR5)

Metrics: How long it takes to confirm the design is functioning properly
Constraint: The final design must be testable
Criteria: The less time required, the better

6 General Solution Approaches

We want to provide a data-driven, intelligent solution to microscopic malarial diagnosis. As we have learned from our stakeholders, we believe that the lack of training and resources severely bottlenecks malarial diagnosis. Since microscopic testing is considered to be highly reliable and influential in the diagnosis results, we have decided to build an intelligent image classification system that creates diagnosis reports directly from slide samples [12].

We settled on applying a deep learning-based method to address microscopic malarial diagnosis as several sources [3, 5, 10] show that this is the rate-limiting step in the diagnosis pipeline. Applying a deep-learning method for image classification would greatly improve the efficiency of the process without compromising its robustness. Furthermore, a software solution to microscopic diagnosis minimally interferes with equipment in the lab.

We also considered non-technical design solutions, such as providing the appropriate training to the workforce that works in these labs; however, this is challenging to implement without intimately involving the clinics themselves in the design process.

It is worth mentioning that other solutions for image classification were also considered. However, they simply do not provide the convenience and result quality that deep learning is capable of

achieving. For example, we also considered using an image booklet containing several diverse images of an infected cell; however, the opinions would still remain subjective and evaluating each slide would take $O(n)$ time.

Other machine learning techniques have also been shown to be outperformed by deep-learning methods in image classification [11]. Since large deep-learning models come with great generalization capabilities, they would also be much more robust to detecting malaria in slide samples that might look significantly different from anything in our datasets.

The main downside that comes with using deep learning is that large deep learning models are known to be black boxes. It is hard to examine a cause and effect relationship and probe the behaviour of the model beyond the inputs and outputs it provides. Although this is a major downside, we will combat this by reporting more informative statistical results that can be more telling of the accuracy of the result.

Even though we can't tell you *why* the model predicted what it did, we can divide our prediction framework in ways such that useful information is still disseminated to the lab technician. This means that although we don't know which set of pixel values are causing a cell to be classified as parasitic, we can still show the technicians the images of the most problematic cells, as well as provide confidence data to give them a better picture of why the results appear the way they do. In this manner, we don't let the algorithm resolve any uncertainties in the diagnosis — we leave that to the trained professionals at the lab. Our solution would merely automate the parts of the diagnosis that require "computer-level" attention to detail.

7 Outcomes and Deliverables

The deliverables for this project will be outlined as multiple *epics*, which outline the major features of the end product. Each *epic* will also contain the associated **Objectives and Key Results (OKRs)** and milestones. The *epics* are as follows:

7.1 Malaria Classification

OKRs: To design for accuracy (HPR1), the classifier should provide results with 80% or higher accuracy and less than 19.4% false negatives. To ensure greater efficiency (HPR4), the wall-clock-time of the program should be less than the original processing pipeline.

Milestones: Train a ResNet model on single-cell data that can correctly identify a cell as infected with malaria; Increase ResNet layers to acheive less than 19.4% false negatives and 80% or higher accuracy while running in less time than the original processing pipeline

7.2 Statistical Robustness

OKRs: Build and test a high precision (HPR2) classification model which returns a confidence interval that bounds at least 80% of the results. To ensure high transparency (LPR2), the product should provide better insight into why the model predicted the diagnosis.

Milestones: Provide a confidence interval for $80\%+$ of all predictions made for cells being tested for malaria

7.3 Report Generation

OKRs: Build software to generate a high transparency (LPR2) report which explains the reasoning of the model's results, including its input and outputs with additional descriptions of the cause/effect process for clarity. To design for interpretability (HPR6), the report should provide enough information to technicians to be able to examine the report, understand the source of the result, and accept or reject the software's diagnosis.

Milestones: Generate a report that contains the original image from the microscope and an appendix with additional images and data outputted by the model to provide full transparency to the technician.

7.4 Slide Segmentation

OKRs: To design for high interpretability (HPR6), the product should segment the slide image into boxes of the parasites, with their associated confidence intervals, in order to make the model's inputs and associated predictions more clear to the technicians. To improve transparency (LPR2), the product should show the technicians where the parasites were detected so they know what the model used to reach its conclusion (cause/effect relationship).

Milestones: Create a feature in the software product (using an ML based approach) that boxes around the parasites in the slide image; Include a subset of the parasite images in the report generation along with their associated confidence intervals

7.5 Microscope Mounting Hardware

OKRs: To ensure high usability (HPR3), the product should allow a technician to attach a camera to a microscope and send the image to the malaria classification model, without additional training.

Milestones: Create and 3D print CAD model of device holder with microscope camera hole; Create or retrofit existing device (phone or Raspberry Pi) to capture images from microscope to send to the model

7.6 User Interface

OKRs: Usability (HPR3): create a user interface that requires no additional training to upload a microscope slide image and review the software's results on the malaria diagnosis. Efficiency (HPR4): the user interface should make it that on average, the time requiP@go to upload a slide image and review results is less than the existing method of getting a malaria diagnosis.

Milestones: Provide a website/application to allow for uploading an image from a smartphone or Raspberry Pi to send to the computer where the malaria classification model is running; Connect the website/application to the malaria classification model to generate and open the report on the computer.

Our priority is to deliver the following *epics* as part of the final deliverable: Malaria Classification, Statistical Robustness, and Report Generation. We also hope to be able to deliver Cell Segmentation and Microscope Mounting Hardware. If the time permits, then we will also deliver a User Interface.

Our final deliverable will include setup documentation, outline how to install our device and software for use in the lab. It will also include a user guide that can be used as a reference to understand how to use our product.

8 Project Management Plan Summary

The following is the list of *epics* (high-level, major features) that the project is divided into. They are described in more detail in the Outcomes and Deliverables section above.

- Develop and fine-tune code (**Malaria Classification**)
- Provide analysis of code accuracy (**Statistical Robustness**)
- Generate report on malaria diagnosis (**Report Generation**)
- Create camera attachment (**Microscope Mounting Hardware**)
- Implement slide segmentation for parasites (**Slide Segmentation**)
- Provide instructions to use solution (**User Interface**)
- Testing and Validation

A summary of the timeline and status of each of these *epics* is provided below:

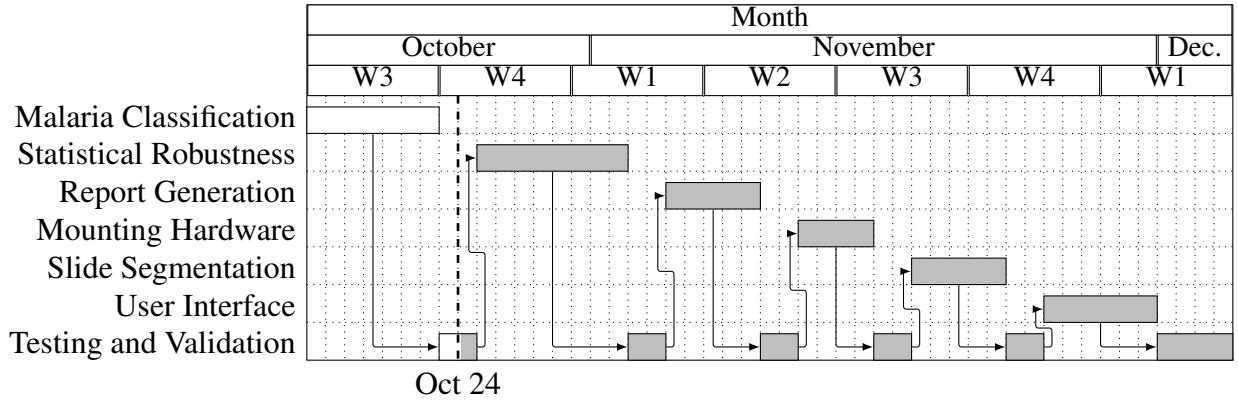

Figure 1: Gantt Chart

We will continue internal meetings for two hours every Monday, Tuesday, and Friday, as well as biweekly meetings with our GSU counterpart on Sundays. We have decided to follow some parts of the agile methodology to structure our project management planning. At the start of each internal meeting on Friday, we start with a scrum stand-up, where each team member explains their progress since the previous meeting, what they plan to do, and if they have any blockers. We will also allocate time for sprint planning and review, in which we plan out the main tasks for the upcoming week for the whole team. See the section "Communication and Schedule" in the Project Management Plan Artifacts for more details.

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Appendices

A Design Consideration Artifacts

When it comes to automating image classification using deep-learning, the most common approach is to simply use a large convolutional neural network (CNN) as a black-box that maps each collection of pixels (an image) to a particular classification. Although in some cases this might be a reasonable solution, in a medical lab setting these models can be really brittle and might introduce a tighter bottleneck into the diagnosis procedure.

Such models, however, are quite popular as they provide really strong classification results on large datasets. Our problem with directly applying such models in this context is that they force a direct compromise between robustness (HPR1, HPR2) and interpretability (HPR6).

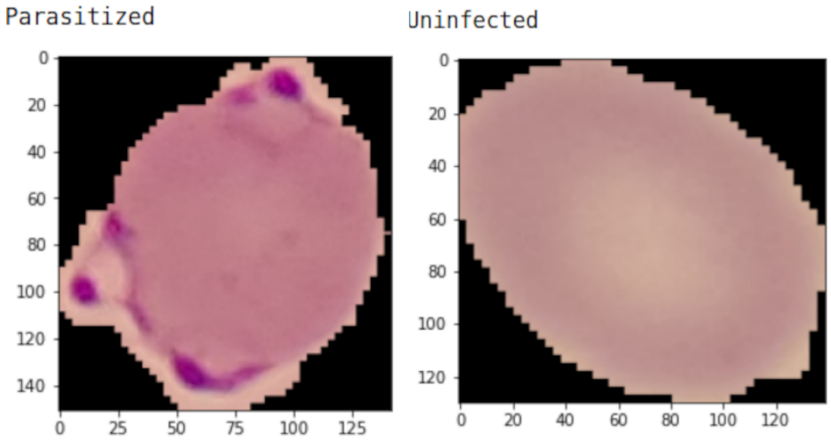

Figure 2: Our preliminary results showing image classification on single blood cells

Our compromise was that we decided to cascade two different machine learning models together to obtain gains with robustness and interpretability. The first model will take in an image of the slide sample and produce segmentation results [4]. This means it would take in a large image of the slide sample and would draw boxes around the regions of the slide that it thinks could be infected. Furthermore, these boxes are also ordered by the confidence of the model. Classical methods from computer vision (such as the watershed algorithm) are used to perform this step, as they are capable

of performing this segmentation reasonably without introducing too many hidden variables that would undermine the reliability of the results.

The second model takes in each one of these regions of the image and tries to identify whether it has malaria or not. This model has already been trained on several images of infected and healthy cells. In our design, this is a large ResNet (a sophisticated CNN that is shown to be performant on image classification). Note how dividing the problem like this allows us to provide descriptive data on how classifications are made (the regions of the images that could contain a parasite) while filtering through them to bring the accuracy of the results up.

Ideally, we would like to build an end-to-end interpretable model for this task. However, such models are still an active area of research and currently don't show strong results [11, 5].

B Project Management Plan Artifacts

B.1 Team Charter

About the Team

- Team name: Teamies
- Team goals: To create a working product from which stakeholders will benefit from
- Shared values: Empathy, novelty, sustainability, efficiency

Project Team Meeting Plan

- Meeting schedule
  - Our team will meet three times per week: twice during studio, and every Friday from 9-11 am
  - Everyone is responsible for adding meetings into their own schedules; if a meeting is at an irregular time, Emily will send a reminder text via Signal
- Ground rules
  - Each team member will make the team aware of an instance that arises where they cannot make the regular meeting time; the team will then refer to our when2meet to decide on an appropriate time to reschedule
  - Each meeting will begin with a quick update from each member regarding any progress on Notion
- Collaboration tools
  - Each meeting will begin with a quick update from each member regarding any progress on Notion
  - when2meet will be used for scheduling meetings
  - Notion will also be used for any other management tasks
- Plan for personal constraints, emergencies, lateness, or other circumstances when work cannot be submitted on time
  - Each team member will openly communicate any scheduling conflicts to the other team members as soon as possible so the workload can be rearranged

Project Roles and Responsibilities

- Emily: Note-taker, timekeeper, researcher, project planner, global team peer liaison, global client liaison
- Charles: Project planner, risk coordinator, issues coordinator, cost coordinator, global team peer liaison, global client liaison
- Amy: Project coordinator, facilitator, presenter, editor
- George: Systems engineer, component purchase coordinator, 3D-print/laser cut liaison
- Nishkrit: Design engineer, technical researcher, presenter, coordinator

B.2 Communication and Schedule

Team Communications

- The agreed frequency of communication will be at least once per week with weekly in-person team meetings
- Progress will be communicated via Signal, Notion, and verbally during team meetings
- Communication issues will be addressed on Notion via the Roadmap page; issues can also be brought up during team meetings (an extra meeting may be scheduled if the issue is of high priority)
- A data dictionary for interdisciplinary terms will be kept on the Jargon page on Notion

Project Schedule

- Milestones and deadlines will be kept on the To-Do and Roadmap pages on Notion
- Emily will be in charge of updating the schedule on the Roadmap
- An issues log will be kept on the To-Do page with each issue flagged as a "bug"

B.3 Risk Management Plan

Risk	Risk Description	Risk Category	Probability	Priority	Potential Impact on Desi...	Strategy	Risk Response
COVID-19	Risk for Getting COVID if getting together too often with numerous stakeholders	Disease	Medium	High	Would slow down team's operation	50/50 Online and in-person meetings	Re-Distribute each team member's task
Costs	Risk for not considering the total cost of the design solution	Cost	Low	High	Unable to build the design because of the budget issue	Take costs into consideration in every step when forming the solutions	Reduce the total cost of the design if had to
Technical	Final Design does not meet Stakeholder's Need	Technical	Medium	High	The overall framing and designing process could go well but missing the point of the design in the end, which could result in a failure design.	Take a step back and think about the overall goal more frequently during each step	
Fabrication Risk	Risk for mis-fabricating prototypes	Technical	High	High	The Final Design could not function well	Carefully examine every measure we have before prototyping	Re-Prototype
Long horizon feedback plans	Risk for changing long-term goals if feedback	Planning	Medium	Medium	Slow down the design process, keep redefining the goals but not many progress made	Make the goals more short-term, like weekly goals and daily goals.	Shorten the durations of each goals, make sure each goals is achievable and doable in a week.

Figure 3: Our Risk Management Plan

B.4 Stakeholder Management

- The key external stakeholders include:
  - e-Health Africa clinics
  - Tolulope Oginni
  - Equipment manufacturers
  - University of Toronto
  - Georgia State University
- The preferred method for engaging with the external stakeholders is via the FaCT
- We will communicate with the GSU student biweekly via email and Zoom

B.5 Decision-Making

Decision-making and approach to conflict:

- Discussions will be facilitated using the following four steps:
  1. identify problems
  2. generate alternatives
  3. reach a decision
  4. follow-up
- To make decisions, the team will:
  - Be open to one another's ideas
  - Adapt a decision-making process that everyone agrees on before proceeding to make a final decision
  - Use the FDCR Model
  - Set internal deadlines to facilitate the decision-making system
  - Have a clear timeline of the project, when to do what, when to make decisions and etc.
- Process for making decisions when the team is not in agreement:
  - Everyone will take a step back and analyze the pros and cons; then the team will vote
  - A mediator will cool down the conflict
  - Everyone will be empathetic, have a mutual understanding of other's perspectives, and try to understand from another person's perspective
  - The team will always have backup alternatives to each idea; if one idea is not working, the team will then move to the alternatives upon which everyone has agreed

B.6 Scope, Cost, and Procurement

- Amy and Nishkrit will be in charge of monitoring the project's scope
- Charles will be in charge of the budget and any costs required for the project
- Charles and George will be in charge of procuring any items needed