SENG402 Retinal Imaging Project Plan

Yiyang (Jessie) Yu
Computer Science and Software Engineering
University of Canterbury
Christchurch, New Zealand
yyu69@uclive.ac.nz

Andrew Bainbridge-Smith
Computer Science and Software Engineering
University of Canterbury
Christchurch, New Zealand
andrew.bainbridge-smith@canterbury.ac.nz

***Index Terms*—Retinal Imaging, Computer Vision, Image Classification, Supervised Learning, Deep Learning, Image Quality, Diabetic Retinopathy, Fundus.**

I. Context

Diabetic retinopathy (DR) is a leading global cause of vision impairment [1] that can be prevented by early detection, periodic retinal screenings, and medical treatments [2]. As diabetes prevalence continues to rise globally, it is critical to ensure that the future of our health system can keep providing prompt access to diabetic retinal screenings. By 2040, more than 600 million people (aged 20-79 years) are projected to live with diabetes [3], where they would need treatment with regular screenings. The current screening process in New Zealand involves using a digital camera to collect retina images, which require reading from a trained professional. This manual process involves a time buffer to resource a professional for a diagnostic result. A patient's time is also valuable. Human errors in manual reading that require a patient to come back into the clinic again can also decrease patient engagement with the health system, delaying potential treatment. The dependency on professionals to read images accurately is a stressful bottleneck to the number of patients the system needs to expand to manage.

Automating the screening process for patients can free up resources and professionals' time to attend to other medical areas needing their care. Predictive technology can aid in this screening process to detect and grade the severity of the disease. Related studies have explored fundus images of diabetic retinopathy diagnosis for many years but have not succeeded. However, modern advances in deep learning and classification techniques offer significant promises to support fundus images with retinal gradings [4]. This research will investigate if deep learning solutions can aid in DR screening to lessen the dependency on professionals.

II. Objectives

Technology-aided screening can help provide information on the needed treatment plan to slow and reduce the effects of DR. Diagnosis involves grading the severity of the disease. Deep learning classifiers can extract features in fundus images to automate the grading of DR.

Deep learning requires a large dataset for its training. Fortunately, this study has access to an extensive retinal image database through collaborative work with the University of Otago and the Canterbury District Health Board; however, the images still need to be labelled with retinal grades. An existing web application will be extended to collect labelled data for supervised learning by providing an interface for medical professionals to assess retinal grading.

The assessment made by a professional must be reliable to train the deep learning model. Reliability means if the assessment were repeated to the same medical professional again or to another medical professional, the results would be consistent. To ensure there is consistency in an individual assessment between themselves and between others, the first two research questions ask;

RQ1: What is the statistical consistency of retinal grade assessments made by medical professionals compared with themselves?

RQ2: What is the statistical consistency of retinal grade assessments made by medical professionals compared to each other?

To investigate how deep learning solutions compare with manual grading, the last research question asks;

RQ3: What is the statistical consistency of retinal grade assessments made by deep learning models compared to medical professionals?

III. Plan

Table I and Table II outlines the milestones and associated risks, respectively.

References

[1] W. H. Organization, "Blindness and vision impairment," Available at https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment (2022/10/13).

[2] N. E. I. National Institutes of Health, "Diabetic retinopathy," Available at https://www.nei.nih.gov/learn-about-eye-health/eye-conditions-and-diseases/diabetic-retinopathy#section-id-10543 (2022/07/08).

[3] K. Ogurtsova, J. da Rocha Fernandes, Y. Huang, U. Linnenkamp, L. Guariguata, N. Cho, D. Cavan, J. Shaw, and L. Makaroff, "Idf diabetes atlas: Global estimates for the prevalence of diabetes for 2015 and 2040," *Diabetes Research and Clinical Practice*, vol. 128, pp. 40–50, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168822717303753

[4] N. Tsiknakis, D. Theodoropoulos, G. Manikis, E. Ktistakis, O. Boutsora, A. Berto, F. Scarpa, A. Scarpa, D. I. Fotiadis, and K. Marias, "Deep learning for diabetic retinopathy detection and classification based on fundus images: A review," *Computers in Biology and Medicine*, vol. 135, p. 104599, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0010482521003930

TABLE I
TIMELINE OF PROJECT MILESTONES.

	Milestone	Approach	Tangible outcome(s)	Risk	Due
M1.	Project plan submission.	Research the background surrounding my project to make plans for approaching a goal.	Deliver a project plan to guide the research.	R1.	24 MAR
M2.	Resource set up.	Seek access to research data, retinal images, code repositories, and OpenCV.	A local development environment is ready with the resources necessary for further research work.	R2.	31 MAR
M3.	Collect grade-labelled data.	Source ethic approval and medical professionals. Extend the current web application's capabilities for users to grade retina images.	Dataset of label data to answer RQ1, RQ2, and RQ3 and for training supervised deep learning.	R3, R4.	01 MAY
M4.	Computer vision feature identification.	Research and use techniques in computer vision to identify features from retinal images.	Produce artefact of relevant research and results for the interim report. Code artefacts of computer vision techniques for deep learning models.	R2, R5, R6.	01 MAY
M5.	Initial deep learning model.	Demo to supervisor to evaluate the solution and get feedback.	Document of improvement steps to enhance the deep learning model when answering RQ3 in the final report. Code artefact to refine in the final deep learning model. Produce results for statistical analysis to answer RQ3.	R2, R6.	10 MAY
M6.	Statistic analysis.	Use statistics to evaluate the consistency of repeated assessments by professionals and the deep learning model.	The outcome of RQ1, RQ2 and RQ3 are artefacts for the interim report's results.	R2, R6.	20 MAY
M7.	Interim report submission.	Include an updated project plan and the first results of RQ1, RQ2, and RQ3 in the report.	Delivery of the interim report as a starting point for the final report.	R1.	02 JUN
M8.	Final deep learning model.	Enhance the initial model from M5's demo feedback.	Answer to RQ3 as an artefact for the final report.	R2, R6.	20 AUG
M9.	Abstract submission.	Use the abstract template on learn and submit it as a YAML file with a text extension.	Delivery of an abstract for content in the showcase booklets.	R1.	15 SEP
M10.	Poster submission.	Note down target audiences to prepare an A1-size poster with the main results.	Delivery of a project poster for the University of Canterbury's College of Engineering Showcase.	R1.	02 OCT
M11.	Presentation submission.	Practise a pepaha.	Delivery of slide pack for the project presentation.	R1.	12 OCT
M12.	Final report submission.	Evaluate all results into a scientific report.	Delivery of a final scientific report.	R1.	20 OCT
M13.	Knowledge transfer material.	Prepare and proofread the code repository, documentation, and resources to ensure the continuation of the research's knowledge.	Produce an outline of the project to transfer knowledge. Software-related artefacts will be shared in a research demonstration.	R1.	20 OCT
M14.	Demonstration submission.	Four weeks prior, arrange a meeting with the supervisor and a second marker to inspect the research's software-related artefacts.	Completed a feedback form.	R1.	20 OCT

TABLE II
RISK ANALYSIS FOR THIS STUDY

	Risk	Associated milestone(s)	Contingency plan
R1.	Time stress to finish submissions.	M1, M7, M9, M10, M11, M12, M13, M14. Assignment deadlines from other university courses, sicknesses and poor time planning can bring difficulties in finishing submissions.	A large submission is divided into smaller tasks and represented as iterative deadlines in my calendar. Blocks of time are also scheduled for working towards these small task deadlines and hold me accountable for the time I'd need to block out to achieve the milestones on time.
R2.	Technical difficulties.	M2, M4, M5, M6, M8. Needing more technical knowledge can lead to feeling stuck and hinder progress.	Set up weekly catch-up meetings with the supervisor and communicate honest progress and blockage to get the best support and guidance on potential methods to approach the research.
R3.	Delay in getting ethics approval.	M3. Difficulty in getting the appropriate paperwork and process ready due to lack of experience in this area.	Noted as a high priority and urgent task item to complete compared to other tasks. Communication updates with the supervisor cc'd into email so progress can be pushed forward.
R4.	Scope creep in the data collection method.	M3. The web interface for collecting labelled retinal grading can be difficult and disengaging for professionals to input their assessments. Users making frequent decisions via mouse-clicking of drop downs, radio buttons, or input fields may experience decision and user experience fatigue. Therefore the web interface can be a medium influencing the results of the data labelling, changing the scope of the research to improve upon the user interface.	Ask the users after their labelling how their experience was. Their answer will be shared with the supervisor during the weekly catch-ups. If any influences to the data collection method were identified, discussions would be made on the scope to keep progressing the overall motivation.
R5.	Uncertainty with computer vision technicalities.	M4. Due to a novice experience in the computer vision domain.	Mitigate by practising computer vision lab in the university break so I can gain awareness of existing techniques in computer vision. Visiting computer vision labs and setting up weekly stand-ups with computer vision experts to get efficient support.
R6.	Output different than expected.	M4, M5, M6, M8. Due to novice experience anticipating the unexpected in the research domain.	Prepare for flexibility and potential adaptations to the project's plan. Work on appropriate response plans through honest communication during weekly catch-ups and stand-ups with the research supervisor and computer vision experts.