Project Proposal

**Abstract**

According to WHO’s World Report on Vision 2019 highlights the global prevalence of vision impairment. Currently there are at least 2.2 billion people around the world. Out of the 2.2 billion, there are at least 1 billion cases preventable or yet to be addressed. This points to a significant, urgent need for improved eye care services worldwide. Challenges include geographical disparities of eye care access and a good quality diseases prevention, treatment, rehabilitation service. Additionally, some vision impairment also indicates some early signs of diverse range of other condition non-relating to ocular diseases.

To address the gap, there is a call for improved, accessible for medical image analysis. A major factor that could mitigate these challenges is the early detection and diagnosis of ocular diseases, which can prevent further visual impairment. We hope to leverage deep learning to classify common ocular diseases automatically while also exploring biomarkers that could aid in the early detection of these conditions, specifically, DR (Diabetic Retinopathy), MH (Media Haze), ODC (Optic Disc Cupping), TSLN (Tessellation), DN (Drusen), MYA (Myopia), ARMD (Age-related Macular Degeneration), and Normal. By combining classification with biomarker analysis, we hope to address both immediate diagnostic needs and the potential for proactive healthcare.

**Reference:**

* [**https://ieeexplore.ieee.org/document/10493693**](https://ieeexplore.ieee.org/document/10493693)
* [**https://www.who.int/publications/i/item/9789241516570**](https://www.who.int/publications/i/item/9789241516570)
* [**https://www.mdpi.com/2075-4418/13/6/1081**](https://www.mdpi.com/2075-4418/13/6/1081)

**Data Set**

* **Retinal Fundus Multi-Disease Image Dataset (RFMiD):** 3203
  + **Train:** 1921
  + **Validation:** 641
  + **Test:** 641
  + **Diseases:** 45

**State-of-the-Art**

* EyeDeepNet: a customed CNN the extracts features from images to identify patterns associated with various retinal diseases and classification.
* Data Type Conversion
* Normalization: 0-255 -> 0-1
* Shuffling
* Train-Test-Split
* Augmentation: image rotation, shearing, and horizontal flipping

**Proposed Plan (Comparing the result with different systems and approaches, ultimately to improve the result from the previous paper)**

* Model vs. Model:Unet vs State-of-the-art
* Data Type Conversion
* Resizing:512 x 512
* Normalization:0-255 -> 0-1
* Augmentation:
  + Image rotation
  + Shearing
  + Horizontal flipping
  + Histogram equalization: Contrast Limited Adaptive Histogram Equalization (CLAHE)
  + Discrete Wavelet Transform (DWT) Transformation
* Shuffling

**Potential Risks**

Compute Resource Constraints: One risk is the potential lack of sufficient computational resources, especially given that the project may involve real-time processing of sensor data and short video clips. To mitigate this risk, we have outlined several fallback strategies:

* Smaller Models: If the resources are constrained, we can initially train on smaller datasets or reduce the complexity of the models by adjusting hyperparameters such as batch size, model depth, and feature space size.
* Transfer Learning: Another option is to employ transfer learning with pre-trained models, such as using models that have already been trained on similar data (e.g., activity recognition models). This will significantly reduce the time and resources required to train models from scratch.
* Cloud Services: If local resources are insufficient, we can also consider cloud computing platforms like AWS or Google Cloud, which allow scaling up on-demand. However, we will need to manage budget constraints if cloud services are used.

Data Availability: If there are issues collecting or processing sensor data from the pets, we will simulate data using generative models or datasets from previous studies that cover similar topics (e.g., gait monitoring in animals). This allows us to continue testing and refining our models even if the real-world data is delayed.

**Project Timeline and Division of Labor**

Timeline:

* Week 1-2: Project Setup and Data Acquisition
  + Set up the project environment, including required software and tools.
  + Acquire the dataset of ocular disease images, ensuring it contains the necessary conditions: Diabetic Retinopathy (DR), Media Haze (MH), Optic Disc Cupping (ODC), Tessellation (TSLN), Drusen (DN), Myopia (MYA), Age-related Macular Degeneration (ARMD), and Normal.
  + Shawn Pan: Preprocess the collected data by performing image augmentation, normalization, and formatting to fit the deep learning models.
* Week 3-4: Initial Model Development
  + Mino Cha: Start developing the deep learning model architecture for classifying ocular diseases.
  + Shawn Pan: Finalize preprocessing steps and prepare the training and test datasets.
  + Team: Ensure proper documentation and data management practices are in place.
* Week 5-6: Model Training and Initial Testing
  + Mino Cha: Train the deep learning model on the preprocessed data. Run initial tests to evaluate the performance of the model.
  + Ray Zhao: Begin identifying potential biomarkers from the medical images that may correlate with early detection of the diseases. Perform feature extraction and conduct exploratory analysis.
* Week 7-8: Model Refinement and Biomarker Integration
  + Mino Cha: Refine the deep learning model, adjusting hyperparameters, optimizing the architecture, and addressing any overfitting/underfitting issues.
  + Shawn Pan & Ray Zhao: Integrate biomarker findings into the deep learning model or develop additional insights from the biomarker analysis.
  + Team: Review and analyze the model’s performance. Focus on combining classification with biomarker detection.
* Week 9: Final Testing and Evaluation
  + Mino Cha: Conduct final model testing on the full dataset, ensuring the model performs well across all disease categories.
  + Ray Zhao: Finalize the biomarker analysis and validate its integration with the classification model.
  + Shawn Pan: Ensure all data preprocessing, feature extraction, and augmentation methods are properly documented.
  + Team: Evaluate model performance, and assess both classification accuracy and biomarker detection efficacy.
* Week 10: Report and Presentation Preparation
  + Team: Compile all results, including model performance, biomarker analysis, and potential applications in real-world scenarios.
  + Shawn Pan: Lead the writing of the final report, ensuring all sections (data processing, model development, biomarker analysis, and conclusions) are cohesive.
  + Prepare a presentation to share the findings, highlighting the significance of combining deep learning with biomarker analysis for ocular disease detection.

Division of Labor:

* **Shawn Pan**: Focuses on data collection and preprocessing. Shawn will gather and preprocess the medical images required for training and testing the deep learning models. This includes tasks such as image augmentation, resizing, and ensuring the dataset is balanced and ready for model input.
* **Mino Cha**: Handles deep learning model development. Mino will be responsible for creating, training, and fine-tuning the deep learning models for classifying ocular diseases. This includes the implementation of the neural network architecture, training procedures, and hyperparameter tuning.
* **Ray Zhao**: Leads the biomarker analysis. Ray will focus on identifying and analyzing potential biomarkers in the medical images that could indicate early signs of ocular diseases. They will use feature extraction techniques and collaborate closely with Mino to integrate these biomarkers into the classification process.