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| HIGH LEVEL DESIGN DOCUMENT  AI Based ROP Detection  UE20CS390A – Capstone Project Phase – 1  ***Submitted by:***   |  |  | | --- | --- | | **Atharva S Gadad**  **Ayush Gupta**  **Ayush Govind**  **Dhruv Jyoti Garodia** | **PES1UG20CS088**  **PES1UG20CS095**  **PES1UG20CS096**  **PES1UG20CS527** |   Under the guidance of   |  | | --- | | **Dr. Gowri Srinivas**  Professor  PES University |   **January - May 2023**  **DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**  FACULTY OF ENGINEERING  **PES UNIVERSITY**  (Established under Karnataka Act No. 16 of 2013)  100ft Ring Road, Bengaluru – 560 085, Karnataka, India |

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# Note:

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| **Section – 1 & Section 2** | **Common for Product Based and Research Projects** |
| **Section 3 to Section 11** | **High-Level Design for Product Based Projects.** |
| **Section 12** | **High-Level Design for Research Projects.** |
| **Appendix** | **Provide details appropriately** |

# Introduction

When infants are born prematurely, their bodies may not fully develop and their immune systems may be weak, making them vulnerable to external threats. One potential consequence is retinopathy of prematurity (RoP), where the growth of blood vessels in the eye becomes abnormal, potentially leading to blindness. This study focuses on automating the detection of RoP stages by analyzing the formation of ridges, which can help healthcare professionals identify the condition earlier and provide appropriate treatment. The aim is to support nurses, technicians, and doctors in their efforts to detect RoP as early as possible.

Our primary concept involves creating a web-based application that allows healthcare staff and technicians to input fundus images for RoP stage classification. The application will be designed to have a user-friendly interface that is easy to navigate, ensuring that even individuals from remote areas in India can use it with minimal difficulty. The user can submit the fundus image by uploading it to the web application's drop box or by using the upload button. The model deployed on the cloud will process the image and generate a screening report.

The web application will feature a user login system based on the clinician's ID. The interface will be designed with a focus on user-friendliness. For new patients, the user will be prompted to enter patient details such as name, sex, age, and contact number, which the application will assign a patient ID to. If a patient returns for follow-up screening, the application will be able to retrieve their previous details. Users can upload fundus images to the application via a dropbox. The application will be able to generate a screening report based on the uploaded image.

One potential challenge is unreliable internet connections in remote areas, which may affect the usability of the web application. Additionally, the speed of the user's internet connection may impact the time it takes for the model to process the fundus image on the cloud. The size of the images, in terms of pixel count, may also affect the time it takes for the image to be uploaded and processed. Another key consideration is the safety and security of medical reports, as these are highly sensitive pieces of information. Appropriate measures must be taken to ensure that the application meets industry standards for data security, including measures such as data encryption, secure storage, and access controls.

# Current System

The study[3] by Luo et al. proposes a deep learning-based edge-cloud telemedicine system for screening and diagnosing retinopathy of prematurity in remote areas. The system utilizes ResNet101 and undersampling and resampling techniques for accurate image classification. The combination of AI algorithms with a collaborative edge-cloud architecture enables efficient data processing and transmission while ensuring patient privacy and data security. The system reports significant improvements in detection and diagnosis accuracy, but further research and validation are needed. The proposed system has the potential to improve healthcare delivery in underserved areas and promote equitable healthcare.

Diagram

Description automatically generated

Figure 1: Remote ROP diagnosis system architecture based on cloud–edge collaboration[3]

Another paper[1] “Automated retinopathy of prematurity screening using deep neural networks” by Wang et al. describes the use of deep neural networks (DNNs) for retinopathy of prematurity (ROP) screening. The authors collected a large dataset of retinal fundus images and trained two CNN-based models, Id Net and Gr Net, for binary classification and grading of ROP cases. Both CNNs were based on Inception BN17 Network models and achieved high accuracy comparable to a human expert. The ROP detection algorithm was deployed on the cloud, accessible to 6 hospitals through a web interface, and had an average processing time of 2s per case. The dataset was diverse and extensive, preventing overfitting to specific features. The study highlights the potential of cloud-based DNN systems for efficient and accurate ROP screening in clinical settings.

Our goal is to draw inspiration from the existing state of the art telemedicine systems and build upon them. Considering the significant volume of our data, which encompasses over 4000 visits from 2073 patients, a better performing model can be integrated into our system. Access to cutting edge CNN classifier models such as EfficientNet will allow us to train architecturally superior models to the commonly used ResNet[3] and InceptionNet[1][2] models, that can better leverage and learn information contained within the sheer volume of the dataset.

1. **Design Details**
   1. **Novelty**

* Leverages a much larger dataset comprising of over 50k high quality images to learn the features characterizing RoP to a potentially greater extent.
* Uses cutting edge models such as EfficientNet that have higher benchmark performances than commonly used models like ResNet and InceptionNet.
  1. **Interoperability**
* The cloud deployed model will ideally receive data through the web, from the technician’s web browser/device.
* On receiving the uploaded retinal fundus images, the model runs entirely remotely in inference mode, to generate a class prediction for current patient.
* An automated report is sent back to the client device, detailing the output of the screening test and thus facilitating end to end automation of RoP detection.
  1. **Performance**
* The model would ideally minimize input to output latencies by performing as quick and efficient as possible.
* Different model sizes can be used to balance the tradeoff between speed and quality of results, with priority given to the correctness of results.
* A high reliability is always preferable as the system can then be used according the convenience of medical professionals.
  1. **Security**
* Security measures will be implemented to ensure the integrity of the uploaded data and to prevent access from external parties. The web interface will comply to the applicable security standards and guarantee protection of sensitive information.
  1. **Reliability**
* The system should be online and available 24/7 so that it can be used at any time as per the technician’s convenience. High reliability is maintained by maximizing server uptime and minimizing server downtime.
  1. **Portability**
* The planned cloud based system would support portability as the models are contained in a remote server, and hence the storage and processing requirements of the hardware would be minimal.
  1. **Reusability**
* A continuous loop of data flow is possible, where the newly uploaded images are also used to train the model, thus allowing the model to train incrementally by reusing images uploaded for inference.
  1. **Application compatibility**
* The application will ideally be compatible with any device that possesses a stable internet connection, as long as the device is authorized and a secure connection can be established with it.
  1. **Resource utilization**
* Majority of the cost would relate to the management of the cloud service, that directly handles the hardware and infrastructure costs.
* A sufficient bandwidth internet connection would be utilized to produce results in real time.

# Appendix A: Definitions, Acronyms and Abbreviations

[Provide definition of all terms, acronyms and abbreviations required for interpreting this High Level Design document.]

RoP – Retinopathy of Prematurity

# Appendix B: References

[1] Wang J, Ju R, Chen Y, Zhang L, Hu J, Wu Y, Dong W, Zhong J, Yi Z. Automated retinopathy of prematurity screening using deep neural networks. EBioMedicine. 2018 Sep;35:361-368. doi: 10.1016/j.ebiom.2018.08.033. Epub 2018 Aug 27. PMID: 30166272; PMCID: PMC6156692.

[2] Redd, Travis & Campbell, John & Brown, James & Kim, Sang & Ostmo, Susan & Chan, Robison & Dy, Jennifer & Erdogmus, Deniz & Ioannidis, Stratis & Kalpathy-Cramer, Jayashree & Chiang, Michael. (2018). Evaluation of a deep learning image assessment system for detecting severe retinopathy of prematurity. British Journal of Ophthalmology. 103. bjophthalmol-2018. 10.1136/bjophthalmol-2018-313156.

[3] Luo Z, Ding X, Hou N, Wan J. A Deep-Learning-Based Collaborative Edge-Cloud Telemedicine System for Retinopathy of Prematurity. Sensors (Basel). 2022 Dec 27;23(1):276. doi: 10.3390/s23010276. PMID: 36616874; PMCID: PMC9824555.

# Appendix C: Record of Change History

[This section describes the details of changes that have resulted in the current High-Level Design document.]

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| **#** | **Date** | **Document Version No.** | **Change Description** | **Reason for Change** |
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# Appendix D: Traceability Matrix

[Demonstrate the forward and backward traceability of the system to the functional and non-functional requirements documented in the Requirements Document.]

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| **Project Requirement Specification Reference Section No. and Name.** | **DESIGN / HLD Reference Section No. and Name.** |
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