MACHINE LEARNING APPROACH TO DETECT & ANNOTATE EYE DISEASES USING RETINAL IMAGES

TMP-23-162

Project Proposal Report

Lakshith G. P. R. – IT20165666

B.Sc. (Hons) Degree in Information Technology.

Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology

Sri Lanka

April 2023

MACHINE LEARNING APPROACH TO DETECT & ANNOTATE EYE DISEASES USING RETINAL IMAGES

TMP-23-162

Project Proposal Report

Mrs. Devanshi Ganegoda

(Supervisor)

Mr. Jeewaka Perera

(Co-supervisor)

B.Sc. (Hons) Degree in Information Technology.

Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology

Sri Lanka

April 2023

Declaration

I declare that this is my own work, and this proposal does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any other university or Institute of higher learning, and to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

Name	Student ID	Signature
Lakshith G. P. R.	IT20165666	

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the supervisor   Date

....

(Mrs. Devanshi Ganegoda)

Abstract

There are 463 million diabetic patients worldwide; by 2045, that number will rise to over 500,000. According to projections, this figure will likely be close to 700 million [1]. The prevention and treatment of diabetic complications must be prioritized due to the considerable increase in the population with diabetes. Diabetic retinopathy (DR), one of diabetes's detrimental effects, can cause vision loss if not adequately recognized and managed. To develop treatment strategies and track the development of the illness, it is essential to accurately grade the severity of DR. Calculating the DR's severity requires extensive experience. Several regions need more expertise or resources to solve the current issue. The research suggests the use of a mobile app by eye doctors and medical professionals to evaluate how severe diabetic retinopathy is based on retinal fundus images. The suggested method involves utilizing contemporary convolutional neural networks (CNNs) to identify characteristics, then applying transfer learning and data augmentation techniques to enhance the model's effectiveness. The algorithm's performance will be assessed using accuracy, precision, recall, and F1 score after training on a sizable collection of annotated retinal images containing various DR levels. The long-term objective of this study is to offer clinicians a quick and accurate tool for DR diagnosis and treatment, reducing the burden of vision loss in diabetic patients.

Table of Contents

List of Figures

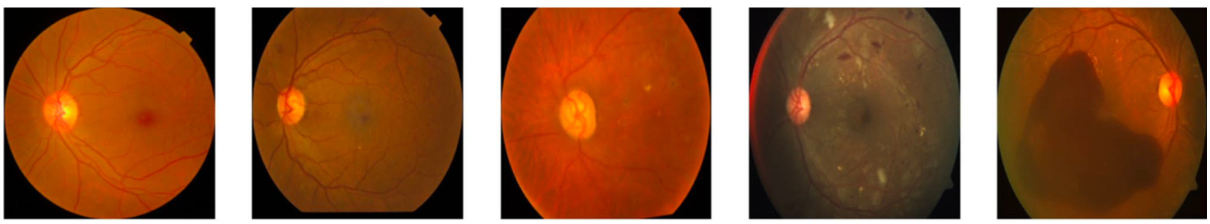
1. Introduction

Background and literature survey

DR, which stands for diabetic retinopathy, is an eye ailment brought about by diabetes and is a major contributor to vision loss and in severe cases, blindness. It has evolved into a significant medical issue on a global scale [2], [3]. This early diagnosis, treatment, and severity monitoring can reduce the number of new DR cases by about 56% [4]. Regular screening initiatives can help achieve this objective. [5]. Hence, the majority of national health organizations advocate for the screening of diabetic retinopathy [5]. Ophthalmologists frequently use retinal fundus images as the primary imaging method to detect and evaluate DR severity, which can serve as an indicator of the disease's progression. But many countries need the expertise, infrastructure, and human resources to facilitate a good screening process. According to research conducted based on the Sri Lankan region, the findings are shown that Colombo district is home to 77.5% (31 out of 40) of the region's 40 board-certified ophthalmologists and six vitreoretinal surgeons [6]. Despite having the highest national DR infrastructure ratios, the Western province still needs a formalized DR screening program [6]. This hole in the healthcare system causes delayed detection and treatment, further escalating DR's threat to public health. Given the importance of DR on a global level and its impact on vision loss and blindness, there is an increasing need to find workable solutions for early diagnosis and treatment.

To determine the stages of DR severity, the ophthalmologist examines fundus images for lesion-based symptoms like microaneurysms, hard/soft exudates, and hemorrhages [7]. The following stages make up the positive DR:

1. mild: the earliest stage capable of containing microaneurysms
2. moderate: in this situation, the blood vessels are unable to transport blood
3. severe: blood vessel blockages may occur in this situation, signaling the growth of new blood vessels.
4. Proliferative: the stage where new blood vessels first form.



Normal (No DR) | Mild DR | Moderate DR | Severe DR | Proliferative DR

Figure 1 – DR classification

The fundus images in Fig. 1 depict various stages of DR severity. The fact mentioned above leads us to conclude that manually grading the DR severity stage on fundus images may result in inconsistencies. As a result, computer-aided techniques have become more prevalent to improve diagnosis and increase the likelihood of early detection [8]. Medical image classification areas such as [9], [10] segmentation of medical image [11], [12], registration of medical image [13], [14] medical image fusion [15], [16] as well as the generation of medical image reports [17] have all benefited from the use of convolutional neural networks (CNNs), which can learn intricate representations in a data-driven fashion. So that this proposed system is powered with CNN and deep learning algorithms, this deep learning-based algorithm's practical design and application for DR severity grading may serve as a model for regions dealing with comparable infrastructure and human resource problems. It is hoped that by disseminating the knowledge and experience gained through this research, a contribution can be made to the global fight against vision loss and blindness caused by diabetic retinopathy, thereby improving the healthcare outcomes of those affected globally.

Research gap

Despite the advances in identifying and diagnosing the severity of diabetic retinopathy (DR), there is a research void regarding the creation of mobile apps that are cost-effective, efficient, and accessible for grading DR severity.

In order to detect nonproliferative diabetic retinopathy, a deep convolution neural network (DCNN) was proposed in [18]. Despite achieving substantial accuracy, there were some concerns identified with this study as outlined below:

- The utilization of preprocessing techniques has been employed to enhance the quality of retinal images and, as a result, improve the accuracy of DR detection.Nevertheless, conventional contrast enhancement techniques frequently introduce noise into retinal images, diminishing their overall quality. This decreased image quality can result in a high rate of false detections and decreased detection accuracy, highlighting the need for more advanced and robust preprocessing methods that minimize noise while preserving crucial image details.

- Feature extraction and nonproliferative diabetic retinopathy detection have employed deep convolutional neural networks (DCNNs). Nevertheless, these networks frequently extract features from the entire image and fail to take into account any specific region of interest (ROI) related to DR. As a result of the algorithm's processing of image regions that are irrelevant to the detection of features, this method may result in high latency. More targeted feature extraction methods that focus on the most relevant regions of retinal images thereby reducing computational complexity and enhancing detection accuracy, are required to address this issue.

- To enhance the effectiveness of the detection process, Principal Component Analysis (PCA) has been utilized to decrease the dimensionality of the identified features. However, the optimal number of principal components must be chosen in order to prevent information loss, which can reduce detection accuracy. Important information related to DR severity grading may be lost if an excessive number of components are removed, thereby hindering the algorithm's performance. Therefore, effective dimensionality reduction techniques that preserve essential information while reducing computational complexity and maintaining detection accuracy are required.

A data augmentation technique was proposed by the authors in [19] to increase the rate of detection of proliferative diabetic retinopathy. However, the following concerns were noted:

- Utilizing Otsu Thresholding for Vessel Segmentation: Vessel segmentation has employed the Otsu thresholding method, which has demonstrated favorable outcomes in some instances. Nevertheless, images with noise do not yield the best results using this method. Thus, to enhance vessel segmentation performance, image noise must be eliminated before thresholding. Otherwise, this method may fail, resulting in less precise vessel segmentation and a reduction in the accuracy of DR grading.

- Diabetic retinopathy detection was achieved through the segmentation of neovessels in the retina as a single feature. However, reliance on a single feature, such as neovessel segmentation, can lead to a high rate of false positives. In order to enhance the precision of DR detection, it is crucial to take into account various features and attributes of retinal images that are related to the disease. This method can aid in reducing false positives and improving the overall performance of DR severity grading algorithms.

- Retinal Image Vessel Segmentation Using U-Net Algorithm The U-Net algorithm has also been used to segment retinal image vessels. Even though it can produce accurate results, learning the vessels from the middle-layer retinal images takes considerable time. This issue causes high latency in the segmentation process, reducing the effectiveness of DR severity grading algorithms overall. There is a need for more efficient vessel segmentation techniques that can reduce computational complexity and processing time while maintaining high detection accuracy for vessels and other relevant features to address this problem.

Using deep learning, Field [20] authors proposed analyzing retinal images to detect diabetes-related eye diseases. The following limitations and challenges in the current approaches to grading the severity of diabetic retinopathy (DR) have been identified:

- Raw Retinal Images for Localization and Segmentation: the proposed system detects eye diseases in diabetic patients using raw retinal images for localization and segmentation. Utilizing raw images can diminish the accuracy of detection and segmentation owing to their poor contrast and noise. Before performing localization and segmentation, it is necessary to preprocess retinal images to improve their quality and reduce noise in order to improve performance.

- Faster RCNN for Feature Extraction: The proposed method implemented the Faster RCNN method for feature extraction. However, the absence regarding the alignment of pixels within the areas of interest led to misalignment, which decreased the precision of detection. To address this issue, It is necessary to develop more precise feature extraction techniques that guarantee proper alignment within the regions of interest, thereby enhancing the detection accuracy of DR severity grading algorithms.

- Class Imbalances in Disease Detection: The proposed method detected various diabetic-related eye diseases. However, the detection process relied on a few trained images, resulting in class imbalances. Class imbalances can harm the performance of the detection algorithm, resulting in less precise identification of various eye diseases. To address this issue, it is essential to collect and curate a more diverse and well-balanced dataset illustrating the various eye diseases affecting diabetic patients. This balanced dataset can train the detection algorithm more effectively, improving its overall accuracy and robustness in identifying diabetes-related eye conditions.

	Mobile application for users	Improved user experience	Greater accuracy	Improved preprocessing techniques	Use of several features for detection
[18]	✗	✗	✗	✓	✓
[19]	✗	✗	✗	✓	✗
[20]	✗	✗	✗	✗	✓
Proposed System	✓	✓	✓	✓	✓

Figure 2 - Research gap

Research problem

Diabetic retinopathy (DR) is a primary global health concern, causing vision impairment and blindness in many people with diabetes. Early diagnosis, precise grading of disease severity, and prompt treatment are essential for preventing the progression of DR and minimizing the associated healthcare burden. Even though several obstacles impede the effective implementation of these measures:

There is a need for more ophthalmologists and vitreoretinal surgeons in numerous nations, making it difficult to provide adequate DR screening and treatment services. A lack of trained professionals can delay disease diagnosis and inadequate management.

Grading the severity of DR requires extensive experience and knowledge. Medical officers and other healthcare professionals involved in DR screening may need more skills, resulting in consistent and accurate grading.

A well-organized DR screening program is essential for early detection and intervention. However, many regions need more infrastructure and resources to implement and maintain such programs. This results in service delivery gaps and suboptimal patient outcomes.

In settings with limited resources, accessing quality healthcare services, such as DR screening, can be challenging due to financial constraints, geographical obstacles, and other socioeconomic factors.
This study aims to develop a mobile application for ophthalmologists and doctors powered by a deep learning-based algorithm for accurately grading DR severity in retinal images to address these issues. By leveraging the power of deep learning, the proposed algorithm has the potential to overcome the obstacles above, resulting in enhanced DR screening, timely intervention, and improved health outcomes for those affected.

OBJECTIVES

Main objectives

The primary aim of this study is to create a mobile-based application powered by a deep learning-based algorithm that accurately grades the severity of diabetic retinopathy (DR) in retinal images, thereby addressing the insufficiency of cost-effective and efficient methods for early diagnosis and management of DR. The algorithm will aid healthcare professionals, allowing them to effectively assess the severity of DRs and make informed treatment decisions. This technology aims to enhance patient outcomes, mitigate vision loss, and decrease the overall burden of DR on healthcare systems.

Specific objectives

To achieve the main objective, the following specific objectives must be met:

This objective requires a comprehensive review of the current literature, clinical guidelines, and expert opinions on DR diagnosis and severity grading systems. By gaining a comprehensive understanding of these systems, the design and development of the deep learning-based algorithm will be well-informed and in line with industry best practices.

Collect and curate a diverse dataset of retinal images: This sub-objective requires the collection of a large and diverse dataset of retinal images representing various stages of DR from a variety of sources. The dataset will be meticulously curated and annotated to guarantee the diversity and quality of the images. This procedure will allow for the efficient training and validation of the algorithm, ensuring its applicability across a variety of patient populations and disease severity levels.

With a solid foundation in DR diagnostic criteria and a diverse dataset, this sub-objective focuses on designing and implementing an innovative deep learning-based algorithm. This algorithm will be designed to accurately identify and grade the severity of DR in retinal images, taking into account a variety of image characteristics and disease-related features.

Evaluating the performance of the developed algorithm entails conducting robust tests and evaluations to assess the algorithm's accuracy, efficiency, and dependability in classifying DR severity. In order to determine the algorithm's efficacy and areas for improvement, it will be compared to conventional methods employed by healthcare professionals and related researchers.

To maximize the impact of the developed algorithm, this objective seeks to examine the practicability, feasibility, and potential barriers to its implementation within existing healthcare systems and DR screening programs. The algorithm can be integrated into clinical practice more effectively by identifying strategies to overcome these obstacles.

Create a user-friendly mobile application for the deep learning-based algorithm: This sub-objective focuses on designing and developing a user-friendly mobile application that incorporates the developed algorithm. The application will enable healthcare professionals and other users to upload retinal images easily, receive DR severity grading results, and track patient progress. A focus will be placed on the app's usability, functionality, and device compatibility, ensuring a seamless user experience and facilitating the algorithm's widespread adoption in clinical practice.

The ultimate objective is to disseminate the research findings, including the developed algorithm, best practices, and lessons learned, to the scientific and medical communities at large. This dissemination will contribute to the global fight against vision loss and blindness caused by diabetic retinopathy, ultimately enhancing the health outcomes of affected individuals around the world.

Methodology

System architecture

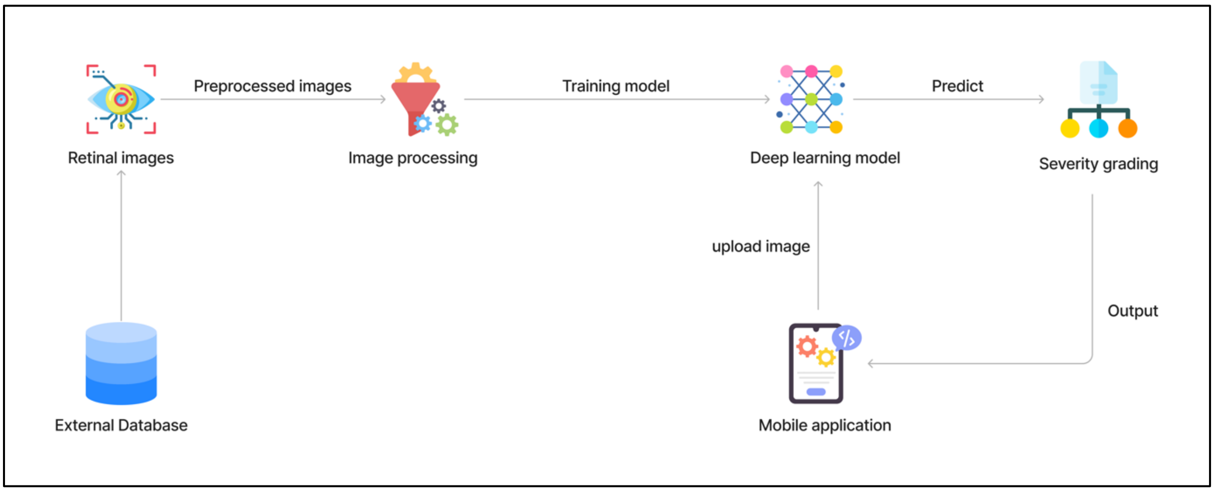


Figure 3 - System diagram

Required data.

The suggested system will undergo training and assessment using the APTOS dataset on Kaggle [21], which is provided by the Asia Pacific Tele-Ophthalmology Society. In each image, a rating of the severity of diabetic retinopathy was provided by a clinician on a graded scale of 0 to 4.

- 0 - No DR
- 1 - Mild
- 2 – Moderate
- 3 - Severe
- 4 - Proliferative DR

Requirements

User requirements

- Intuitive user interface: The mobile app's interface should be easy to use and visually appealing, allowing users with varying levels of technical expertise to navigate and interact with the app effectively.
- Image capture and import: Users should be able to capture retinal fundus images with their smartphone camera and import existing images from the gallery.
- Secure data management: Users must have confidence that their personal and medical information is stored and transmitted securely within the app.
- Step-by-step instructions: The app should provide detailed instructions on capturing and uploading retinal images for analysis.

Functional requirements

- Image preprocessing: Before analyzing the images, the app should preprocess the retinal images to improve quality, reduce noise, and adjust contrast.
- Integration of a deep learning algorithm: The app should include a deep learning algorithm for accurately grading the severity of diabetic retinopathy in retinal images.
- Grading and feedback on severity: The app should provide users with immediate feedback on the detected DR severity level and any pertinent recommendations or next steps.
- Progress monitoring: The app should enable users to monitor the severity of their DR over time, allowing them to see the progression or improvement of their condition.

Non-functional requirements

- Performance: The application should provide efficient and accurate grading of DR severity with minimal latency.
- Scalability: The application must be designed to accommodate a growing number of users and retinal images without compromising performance.
- Reliability: The application should consistently generate accurate and trustworthy DR severity grading results.
- Usability: The application should be accessible to users of all ages and levels of technical expertise.
- Security: The application must protect the confidentiality and security of users' personal and medical information.

System requirements

- Device Compatibility: The application should be compatible with various smartphones, tablets, and operating systems (e.g., iOS and Android).
- Camera compatibility: The app must be compatible with various smartphone cameras to ensure the highest image capture quality for DR analysis.
- Connectivity: The application should be compatible with various network conditions, including Wi-Fi and cellular data.
- Storage: The application should require minimal storage space on the user's device while efficiently handling image and analysis data.
- Update and maintenance: The application should be designed for easy updates and maintenance, enabling the integration of new features, enhancements, and bug fixes.

Gantt chart

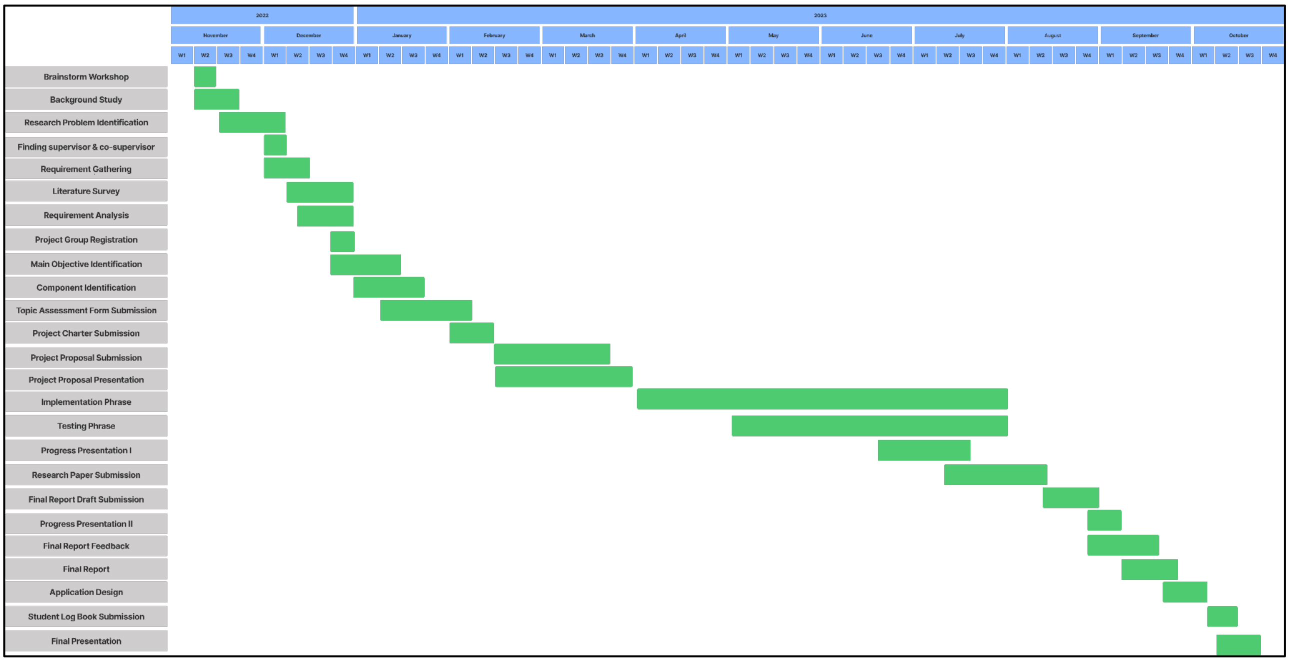


Figure 4 - Gantt chart

Work breaks down structure (WBS)

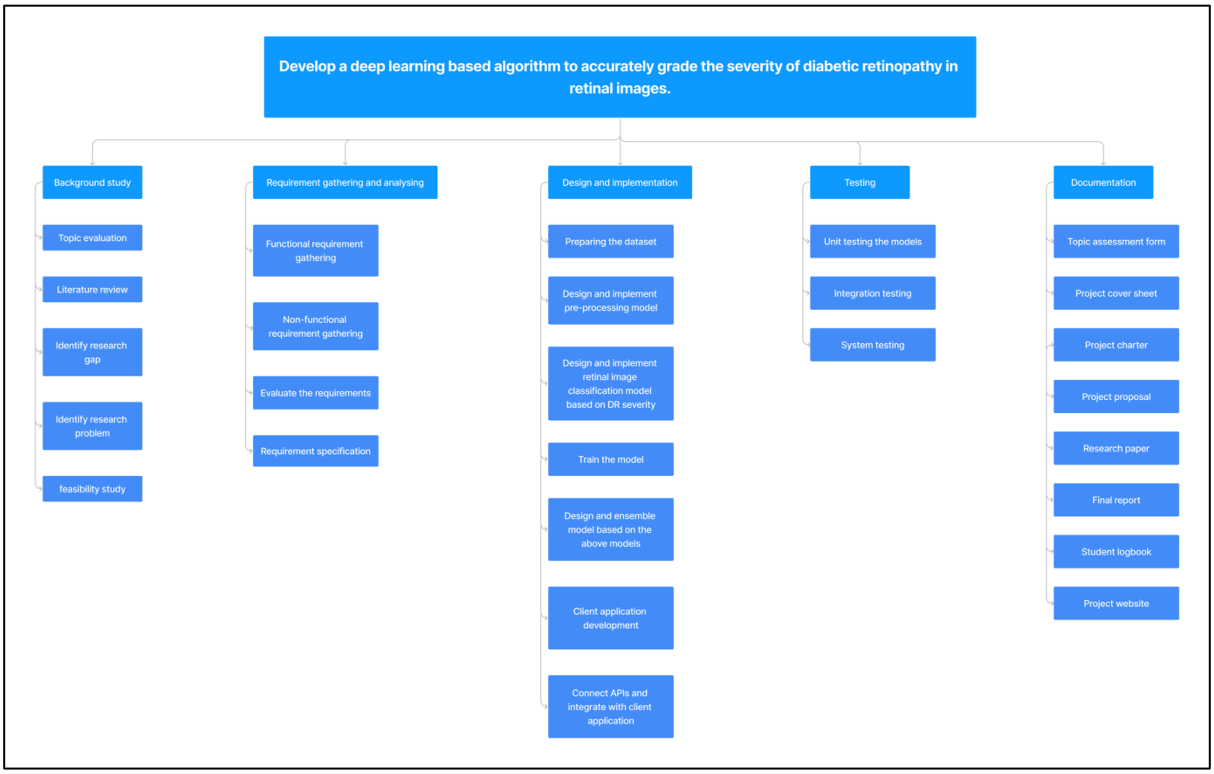


Figure 5 - WBS

Budget and Budget Justification

The hosting budget of 7,000 LKR is designated for purchasing server space and maintaining the app's smooth operation with minimal downtime. This cost includes a dependable hosting service that offers a fast, secure, and scalable environment to accommodate the anticipated user base and efficiently store and process retinal images and user data.

Regular backups are necessary to protect the app's data from loss or corruption. This budget covers the implementation of a secure and efficient backup solution that ensures the safety and integrity of user data, retinal images, and app-related data.

Testing – 2,000 LKR: Extensive testing is required to identify and resolve potential issues, ensuring a high-quality, reliable app for end users. This budget covers the cost of testing tools, resources, and third-party services that help identify and resolve performance, usability, security, and compatibility issues during the development and implementation phases of the application.

Marketing - 5,000 LKR: Effective marketing strategies are required for a successful launch and user adoption of the app. This budget covers the cost of promotional activities such as creating marketing materials, running targeted ad campaigns, engaging in public relations efforts, and attending industry events to increase the app's visibility among potential users and healthcare professionals.

This budget line item accounts for miscellaneous costs that may arise during the app's development, implementation, and marketing phases. These expenses may include software licenses, third-party services, legal fees, and other unanticipated costs.

Total Budget - 21,000 LKR: The budget ensures the successful development, implementation, and commercialization of the mobile app that uses a deep learning algorithm to detect the severity of diabetic retinopathy. This extensive budget enables the app to provide a user-friendly, dependable, and secure solution contributes to the global fight against diabetic retinopathy-related blindness and vision loss.

References

[1] W. Matuszewski, A. Baranowska-Jurkun, M. M. Stefanowicz-Rutkowska, R. Modzelewski, J. Pieczyński, and E. Bandurska-Stankiewicz, "Prevalence of Diabetic Retinopathy in Type 1 and Type 2 Diabetes Mellitus Patients in North-East Poland," *Medicina (Mex.)*, vol. 56, no. 4, p. 164, Apr. 2020, doi: 10.3390/medicina56040164.

[2] R. L. Thomas, S. Halim, S. Gurudas, S. Sivaprasad, and D. R. Owens, "IDF Diabetes Atlas: A review of studies utilising retinal photography on the global prevalence of diabetes related retinopathy between 2015 and 2018," *Diabetes Res. Clin. Pract.*, vol. 157, p. 107840, Nov. 2019, doi: 10.1016/j.diabres.2019.107840.

[3] GBD 2019 Blindness and Vision Impairment Collaborators and Vision Loss Expert Group of the Global Burden of Disease Study, "Causes of blindness and vision impairment in 2020 and trends over 30 years, and prevalence of avoidable blindness in relation to VISION 2020: the Right to Sight: an analysis for the Global Burden of Disease Study," *Lancet Glob. Health*, vol. 9, no. 2, pp. e144–e160, Feb. 2021, doi: 10.1016/S2214-109X(20)30489-7.

[4] B. Tymchenko, P. Marchenko, and D. Spodarets, "Deep Learning Approach to Diabetic Retinopathy Detection:," in *Proceedings of the 9th International Conference on Pattern Recognition Applications and Methods*, Valletta, Malta: SCITEPRESS - Science and Technology Publications, 2020, pp. 501–509. doi: 10.5220/0008970805010509.

[5] T. Y. Wong *et al.*, "Guidelines on Diabetic Eye Care: The International Council of Ophthalmology Recommendations for Screening, Follow-up, Referral, and Treatment Based on Resource Settings," *Ophthalmology*, vol. 125, no. 10, pp. 1608–1622, Oct. 2018, doi: 10.1016/j.ophtha.2018.04.007.
[6] M. M. P. N. Piyseana and G. V. S. Murthy, "Availability of eye care infrastructure and human resources for managing diabetic retinopathy in the western province of Sri Lanka," *Indian J. Ophthalmol.*, vol. 68, no. 5, pp. 841–846, May 2020, doi: 10.4103/ijo.IJO_1754_18.
[7] S. Stolte and R. Fang, "A Survey on Medical Image Analysis in Diabetic Retinopathy," *Med. Image Anal.*, vol. 64, p. 101742, May 2020, doi: 10.1016/j.media.2020.101742.
[8] N. Tsiknakis *et al.*, "Deep learning for diabetic retinopathy detection and classification based on fundus images: A review," *Comput. Biol. Med.*, vol. 135, p. 104599, Aug. 2021, doi: 10.1016/j.compbiomed.2021.104599.
[9] A. H. Masquelin, N. Cheney, C. M. Kinsey, and J. H. T. Bates, "Wavelet decomposition facilitates training on small datasets for medical image classification by deep learning," *Histochem. Cell Biol.*, vol. 155, no. 2, pp. 309–317, Feb. 2021, doi: 10.1007/s00418-020-01961-y.
[10] P. Lakhani and B. Sundaram, "Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks," *Radiology*, vol. 284, no. 2, pp. 574–582, Aug. 2017, doi: 10.1148/radiol.2017162326.
[11] D. Müller and F. Kramer, "MIScnn: a framework for medical image segmentation with convolutional neural networks and deep learning," *BMC Med. Imaging*, vol. 21, no. 1, p. 12, Jan. 2021, doi: 10.1186/s12880-020-00543-7.
[12] H. You, L. Yu, S. Tian, and W. Cai, "DR-Net: dual-rotation network with feature map enhancement for medical image segmentation," *Complex Intell. Syst.*, vol. 8, no. 1, pp. 611–623, Feb. 2022, doi: 10.1007/s40747-021-00525-4.
[13] L. Song, G. Liu, and M. Ma, "TD-Net:unsupervised medical image registration network based on Transformer and CNN," *Appl. Intell.*, vol. 52, Apr. 2022, doi: 10.1007/s10489-022-03472-w.
[14] G. Haskins, U. Kruger, and P. Yan, "Deep learning in medical image registration: a survey," *Mach. Vis. Appl.*, vol. 31, no. 1–2, Jan. 2020, doi: 10.1007/s00138-020-01060-x.
[15] M. Kaur and D. Singh, "Multi-modality medical image fusion technique using multi-objective differential evolution based deep neural networks," *J. Ambient Intell. Humaniz. Comput.*, vol. 12, Feb. 2021, doi: 10.1007/s12652-020-02386-0.
[16] Y. Li, J. Zhao, Z. Lv, and J. Li, "Medical image fusion method by deep learning," *Int. J. Cogn. Comput. Eng.*, vol. 2, pp. 21–29, Jun. 2021, doi: 10.1016/j.ijcce.2020.12.004.
[17] F. Liu, X. Wu, S. Ge, W. Fan, and Y. Zou, "Exploring and Distilling Posterior and Prior Knowledge for Radiology Report Generation," in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA: IEEE, Jun. 2021, pp. 13748–13757. doi: 10.1109/CVPR46437.2021.01354.
[18] J. Wang, Y. Bai, and B. Xia, "Simultaneous Diagnosis of Severity and Features of Diabetic Retinopathy in Fundus Photography Using Deep Learning," *IEEE J. Biomed. Health Inform.*, vol. 24, no. 12, pp. 3397–3407, Dec. 2020, doi: 10.1109/JBHI.2020.3012547.
[19] K. Aurangzeb, S. Aslam, M. Alhussein, R. A. Naqvi, M. Arsalan, and S. I. Haider, "Contrast Enhancement of Fundus Images by Employing Modified PSO for Improving the Performance of Deep Learning Models," *IEEE Access*, vol. 9, pp. 47930–47945, 2021, doi: 10.1109/ACCESS.2021.3068477.
[20] G. G. Rajput, B. M. Reshmi, and I. S. Rajesh, "Automatic detection and grading of diabetic maculopathy using fundus images," *Procedia Comput. Sci.*, vol. 167, pp. 57–66, Jan. 2020, doi: 10.1016/j.procs.2020.03.182.
[21] "APTOS 2019 Blindness Detection." https://kaggle.com/competitions/aptos2019-blindness-detection (accessed Apr. 03, 2023).