KALYANI GOVERNMENT ENGINEERING COLLEGE

FINAL YEAR MAJOR PROJECT

(EC-881)

Mid-Term Progress Report

Electronics and Communication Engineering Department

Project on: Detection and Classification of Diabetic Retinopathy

Acknowledgement

The achievement associated with the successful completion of any task would be incomplete without mentioning the names of those people whose endless cooperation made it possible. Their constant guidance and encouragement made all our efforts successful.

We take this opportunity to express our deep gratitude towards our project mentor, *Dr. Himadri Sekhar Dutta* for giving such valuable suggestions, guidance, and encouragement during the development of this project work.

1. Project Information

1.1 Project title	Identification and Classification of Diabetic Retinopathy
1.2 Group members *(List names along with university roll no. and roles defined for project)*	**Member Name and Roll No.** 1. Ayush Singh — 10200319009 2. Aryan Shaw — 10200319012 3. Mayukh Sen — 10200319014 4. Agni Sain — 10200319019
1.3 Project Guide *(As officially assigned)*	Name: Dr. Himadri Sekhar Dutta Designation: Assistant Professor

1.4 CERTIFICATE

"This is to certify that the progress made in the final year project work until mid-year evaluation held on ____________________, titled as stated in *Sec. 1.1*, executed (as till date) by the students' group mentioned in *Sec. 1.2*, is reflected in this report."	*(Signature of Project Guide with date*

Project insights

1.5 Thematic area(s)	☑ Research ☑ S/W Development ☐ Industry Automation ☐ H/W and circuit development ☐ Other *(please specify)*:
1.6 Keywords *(Max. 3 to 6. Don't use jargon or abbreviation)*	machine-learning, medical-image-processing, python, web development, diabetic retinopathy detection, MobileNet

1.7 Major task(s)	☐ Modeling ☑ S/W Designing ☐ Fabrication ☑ Design ☐ Simulation ☑ Optimization ☐ H/W Designing ☐ Physical tool(s) development ☐ Hardware development ☑ Research & Development ☐ Others *(please specify)*:
1.8 Hardware, Software packages, tools and programming languages used	**Programming Languages** : Python, HTML, CSS, TypeScript **Packages :** TensorFlow, Keras , Scikit-Learn, NumPy, Pandas, Open CV, MobileNet **Frameworks :** Node, Express, EJS. **Tools :** Git, VSCode, Jupyter Notebook,Google Colab

- **Relevant study material**

1.9 Undergrad. courses

(Must be from Electronics & Communication or other Applied Areas.)

	Course code and title
1.	**PE-EC702B** - Digital Image and Video Processing
2.	**OE-EC804A -** Artificial Intelligence
3.	**OE-EC704A** - Web Technology

1.10 Books and other printed material

(Must be easily accessible. Add more rows if required.)

	Title, edition, publishing year and authors' names
1.	Detection and classification of diabetic retinopathy using retinal images , Kanika Verma; Prakash Deep; A. G. Ramakrishnan 2011 Annual IEEE India Conference
2.	Fully Convolutional Architectures for Multiclass Segmentation in Chest Radiographs , Alexey A. Novikov, Dimitrios Lenis, David Major, Jiri Hladůvka, Maria Wimmer, Katja Bühler IEEE Transactions on Medical Imaging (Volume: 37, Issue: 8, August 2018),10.1109/TMI.2018.2806086
3.	Deep Convolutional Neural Network for The Prognosis of Diabetic Retinopathy - Springer (2022)

1.11 Online / web resources ○ (Must be easily accessible. Search engines, social blogs, and unauthentic resources should not be mentioned. Add more rows if required.)	**URL of specific web page** 1. https://www.kaggle.com/code/manifoldix/inceptionv3-for-retinopathy-gpu-hr 2. https://www.kaggle.com/c/diabetic-retinopathy-detection 3. https://www.kaggle.com/competitions/diabetic-retinopathy-detection/data

Objective /Scope

The aim of our project is to develop a software solution to process fundus images and detect Diabetic Retinopathy, the most common eye disease. Our application creates an opportunity for early detection of this disease which means that the chances of recovery will increase and the possibility of vision loss in patients will be reduced in the future. Our target is to create a fundus image processing machine learning model configured to process the model input comprising the one or more fundus images to generate a model output indicative of the patient's health with respect to glaucoma; and processing the model output to generate health analysis data that analyzes an aspect of the patient's health related to glaucoma.

- **Expected outputs**

Aim to detect the presence of diabetic retinopathy in a patient from a sample fundus image of the patient's eye. We classify the eye on the basis of the extent of retinopathy in the eye.

We take fundus images as input and classify the input images on the basis of extent of Diabetic Retinopathy into the following categories based on ICDR Security Level:-

- No Diabetic Retinopathy
- Mild Diabetic Retinopathy
- Moderate Diabetic Retinopathy
- Severe Diabetic Retinopathy
- Proliferative Diabetic Retinopathy

Literature study / Data collection

1. Detection and classification of diabetic retinopathy using retinal images : Retinal images acquired through fundal camera aid in analyzing the consequences, nature, and status of the effect of diabetes on the eye. The objectives of this study are to (i) detect blood vessels, (ii) identify hemorrhages and (iii) classify different stages of diabetic retinopathy into normal, moderate and non-proliferative diabetic retinopathy (NPDR). The basis of the classification of different stages of diabetic retinopathy is the detection and quantification of blood vessels and hemorrhages present in the retinal image. classification of the different stages of eye disease was done using Random Forests technique based on the area and perimeter of the blood vessels and hemorrhages. Accuracy assessment of the classified output revealed that normal cases were classified with 90% accuracy while moderate and severe NPDR cases were 87.5% accurate.

2. Fully Convolutional Architectures for Multi-Class Segmentation in Chest Radiographs : In this paper the authors investigate and propose neural network architectures for automated multi-class segmentation of anatomical organs in chest radiographs, namely for lungs, clavicles and heart. They address several open challenges including model overfitting, reducing number of parameters and handling of severely imbalanced data in CXR by fusing recent concepts in convolutional networks and adapting them to the segmentation problem task in CXR. They demonstrate that our architecture combining delayed subsampling, exponential linear units, highly restrictive regularization and a large number of high resolution low level abstract features outperforms state-of-the-art methods on all considered organs, as well as the human observer on lungs and heart.

- Abstract

Diabetic Retinopathy (DR) grading into different stages of severity continues to remain a challenging issue due to the complexities of the disease. Diabetic Retinopathy grading classifies retinal images to five levels of severity ranging from 0 to 5, which represents No DR, Mild non-proliferative diabetic retinopathy (NPDR), Moderate NPDR, Severe NPDR, and proliferative diabetic retinopathy. With the advancement of Deep Learning, studies on the application of the Convolutional Neural Network (CNN) in DR grading have been on the rise. High accuracy and sensitivity are the desired outcome of these studies. This paper reviewed recently published studies that employed CNN for DR grading to 5 levels of severity. Various approaches are applied in classifying retinal images which are, (i) by training CNN models to learn the features for each grade and (ii) by detecting and segmenting lesions using information about their location such as microaneurysms, exudates, and haemorrhages. Public and private datasets have been utilised by researchers in classifying retinal images for DR. The performance of the CNN models was measured by accuracy, specificity, sensitivity, and area under the curve. The CNN models and their performance varies for every study. More research into the CNN model is necessary for future work to improve model performance in DR grading. The Inception and the EfficientNet model can be used as a starting point for subsequent research. It will also be necessary to investigate the attributes that the model uses for grading.

Introduction

Diabetic retinopathy is a diabetes complication that affects eyes. It's caused by damage to the blood vessels of the light-sensitive tissue at the back of the eye.

Microaneurysms (MA) is usually the first symptom of DR that causes blood leakage to the retina. This lesion usually appears as small red circular spots with a diameter of fewer than 125 micrometers

There are two basic forms of diabetic retinopathy :-

● Proliferative retinopathy: New blood vessels form, but they are unstable, withweak walls, so they may leak fluid or blood. They grow over the retina, which can lead to vision loss.

● Non-proliferative retinopathy: Blood vessels in the retina deteriorate, and then become blocked and deformed. Proteins, fluids, and fats leak out of these vessels and collect in the retina. This causes swelling, which leads to poor visual acuity, or blurry vision.

Symptoms of diabetic retinopathy may include:-

1. Blurry vision.
2. Sudden vision loss in one or both eyes.
3. Black spots.
4. Flashing lights.
5. Trouble reading, seeing detailed work, or seeing other things
6. up close

Methodology

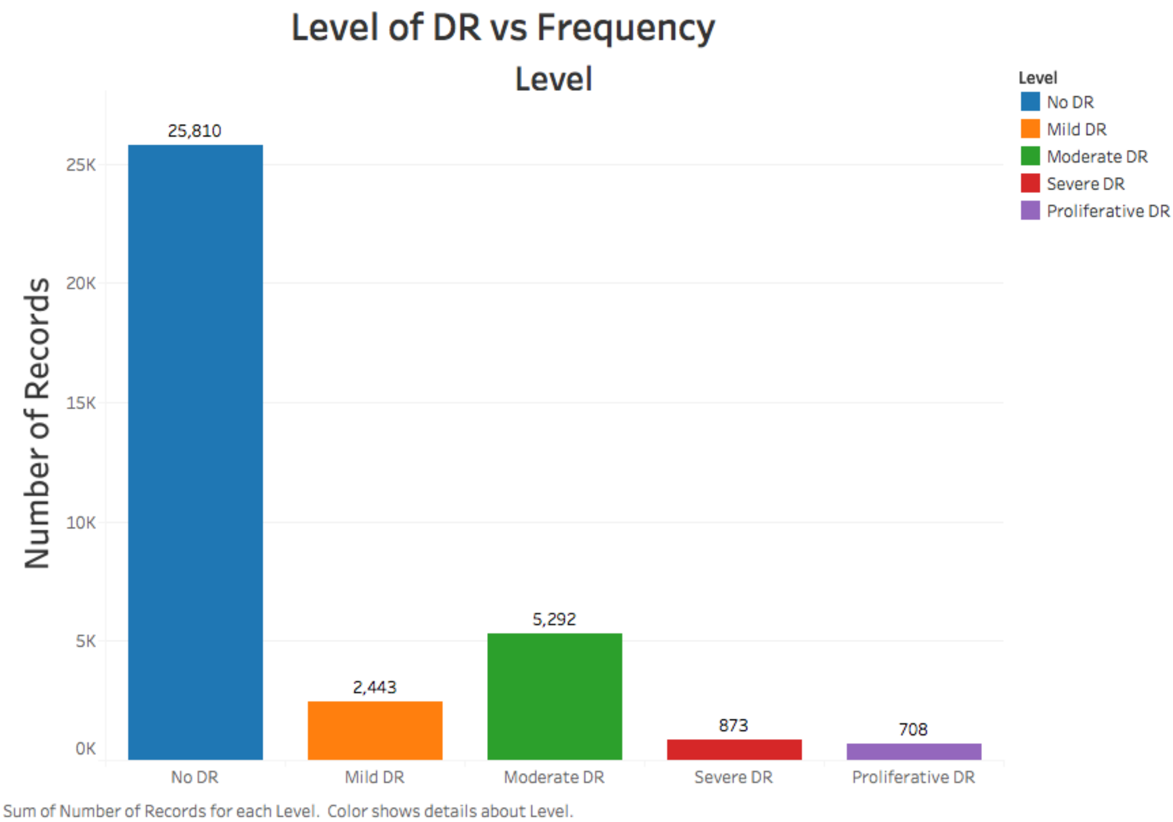
1. **The Data:**

The data originates from a 2015 Kaggle competition. However, is an atypical Kaggle dataset. In most Kaggle competitions, the data has already been cleaned, giving the data scientist very little to preprocess. With this dataset, this isn't the case.

All images are taken of different people, using different cameras, and of different sizes. Pertaining to the preprocessing section, this data is extremely noisy, and requires multiple preprocessing steps to get all images to a useable format for training a model.

The training data is comprised of 35,126 images, which are augmented during preprocessing.

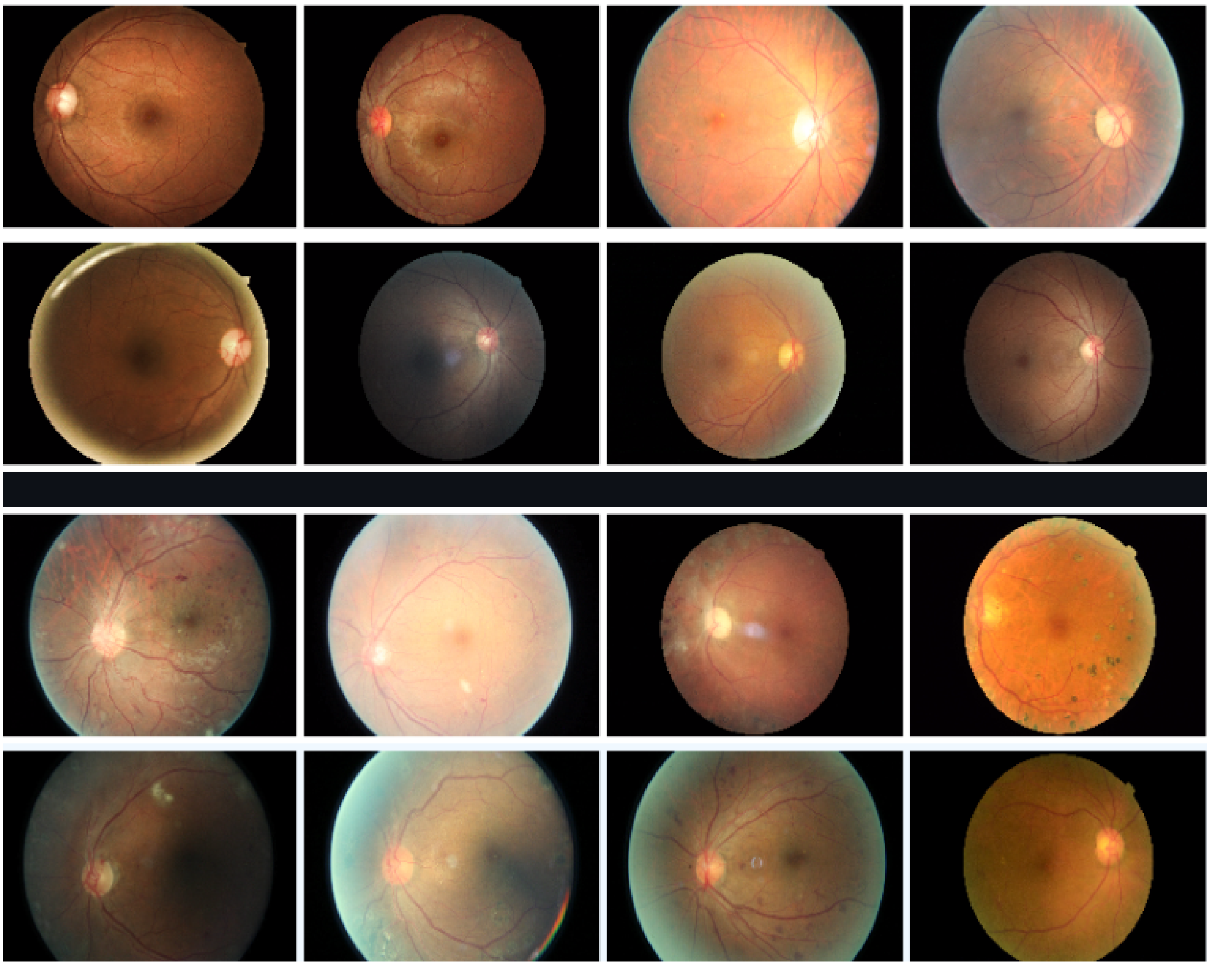
2. **Exploratory Data Analysis :** The very first item analyzed was the training labels. While there are five categories to predict against, the plot below shows the severe class imbalance in the original dataset.



Of the original training data, 25,810 images are classified as not having retinopathy, while 9,316 are classified as having retinopathy.

Due to the class imbalance, steps taken during preprocessing in order to rectify the imbalance, and when training the model.

Furthermore, the variance between images of the eyes is extremely high. The first two rows of images show class 0 (no retinopathy); the second two rows show class 4 (proliferative retinopathy).



3. Preprocessing : The preprocessing pipeline is the following:

1. Download all images .
2. Crop & resize all images using the resizing script and the preprocessing script.
3. Rotate & mirror all images using the rotation script.
4. Convert all images to array of NumPy arrays, using the conversion script.

Crop and Resize All Images

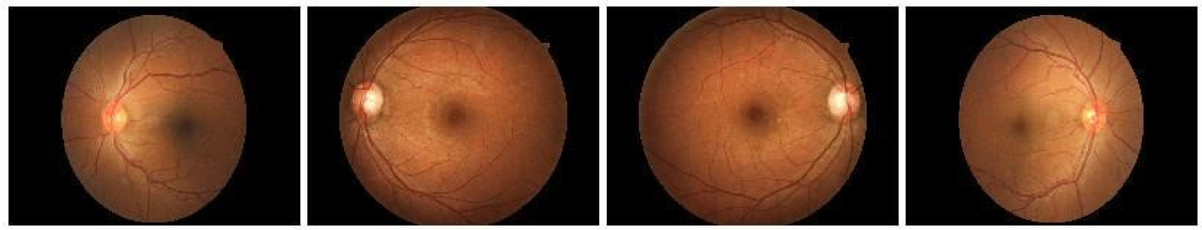
All images were scaled down to 256 by 256. Despite taking longer to train, the detail present in photos of this size is much greater then at 128 by 128.

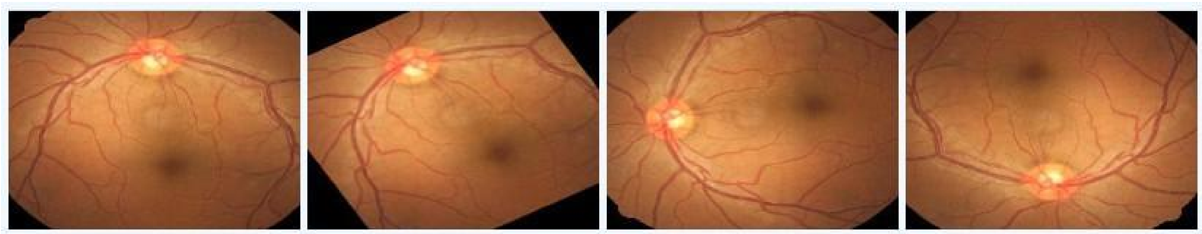
Additionally, 403 images were dropped from the training set. Scikit-Image raised multiple warnings during resizing, due to these images having no color space. Because of this, any images that were completely black were removed from the training data.

Rotate and Mirror All Images

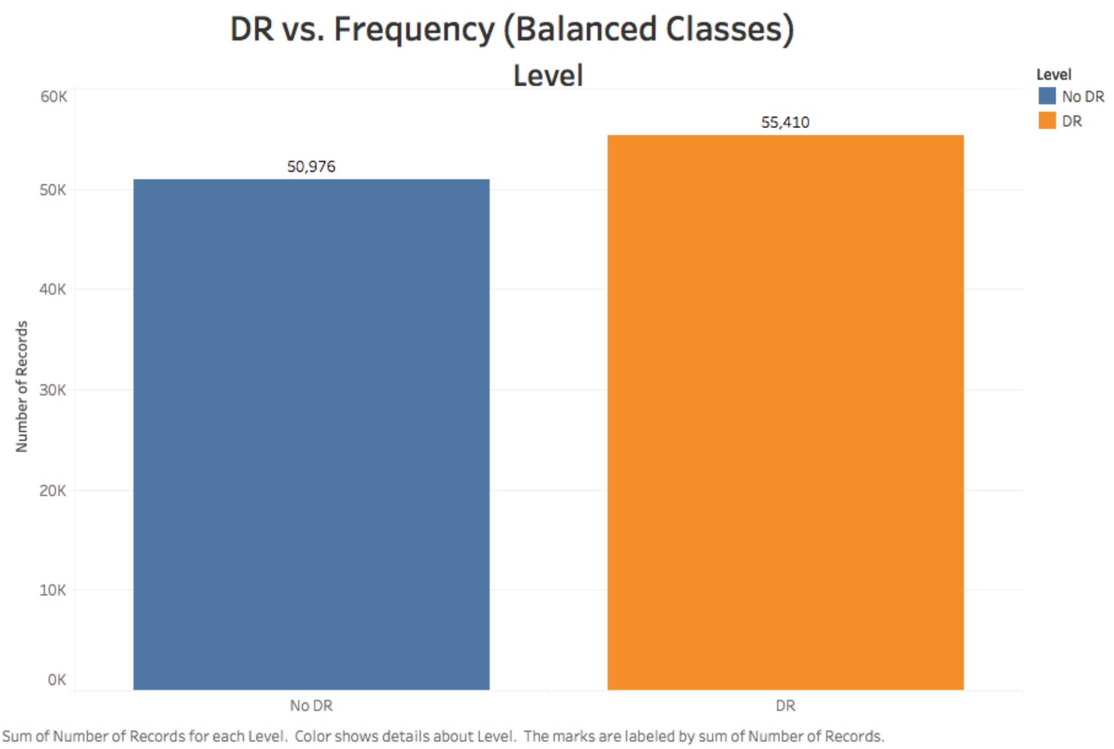
All images were rotated and mirrored.Images without retinopathy were mirrored; images that had retinopathy were mirrored, and rotated 90, 120, 180, and 270 degrees.

The first images show two pairs of eyes, along with the black borders. Notice in the cropping and rotations how the majority of noise is removed.





After rotations and mirroring, the class imbalance is rectified, with a few thousand more images having retinopathy. In total, there are 106,386 images being processed by the neural network.



MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications:

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

MobileNet is a type of convolutional neural network designed for mobile and embedded vision applications. They are based on a streamlined architecture that uses depthwise separable convolutions to build lightweight deep neural networks that can have low latency for mobile and embedded devices.

- **Executed work**

Our work so far includes :-

- Explored and reviewed multiple different datasets to identify the most appropriate one for the project.
- Downloaded and preprocessed the selected dataset by applying various techniques such as rotating, mirroring, and cropping to reduce noise and improve image quality.
- Built a Convolutional Neural Network (CNN) model based on MobileNet architecture using TensorFlow and Keras for image classification.
- Trained the model using the preprocessed dataset to obtain a training accuracy score.
- Tested the model on a separate dataset to evaluate its performance and obtain a testing accuracy score.
- Built a command line interface (CLI) tool to access and use our model from the terminal and get live predictions.
- Built a webapp based on the above easy-to-integrate cli tool to mimic the usage of this model in a medical institute.

- **Remaining work**

We aim to complete the following work in the coming months :-

- Fine-tuning the model: Fine-tuning the model can help improve its performance by tweaking the existing architecture or parameters. The model requires adjusting the hyperparameters or experimenting with different architectures to achieve better accuracy.
- Testing on external datasets: Next step would be to test our model on external datasets to evaluate its performance on unseen data. This can help identify potential issues and improve the model's accuracy.
- Deploying the model: We are considering to deploy the model and the webapp on a cloud server for wider accessibility.
- Collaborating with medical professionals: It could be useful to collaborate with medical professionals to obtain feedback on the model's performance and incorporate their insights into the development process

References

- S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider and R. Deters et al, "A hybrid deep learning architecture for leukemic lymphoblast classification", 2019.
- Varun Gulshan, Subhashini Venugopalan and Rajiv Raman, "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs", *JAMA*, vol. 316, no. 22, pp. 2402-2410, 2016.
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- R Borys Tymchenko, Philip Marchenko and Dmitry Spodarets, *Deep Learning Approach to Diabetic Retinopathy Detection*.
- https://www.kaggle.com/c/diabetic-retinopathy-detection/data
- Fully Convolutional Architectures for Multiclass Segmentation in Chest Radiographs , Alexey A. Novikov, Dimitrios Lenis, David Major, Jiri Hladůvka, Maria Wimmer, Katja Bühler IEEE Transactions on Medical Imaging (Volume: 37, Issue: 8, August 2018),10.1109/TMI.2018.2806086

Evaluation by the evaluation panel

	Remarks by project Guide (if any)	Remarks from the evaluation panel members
Overall Performance & Scope of Improvement		