Deep Learning Fundus Image Analysis for Early Detection of Diabetic Retinopathy

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Content

1. Introduction

Diabetic Retinopathy (DR) emerges as a prevalent complication of diabetes mellitus, inducing retinal lesions that impede vision. This condition, if left undetected in its early stages, poses a grave risk of irreversible blindness. Despite the absence of a cure, timely treatment plays a pivotal role in sustaining vision. However, the conventional approach to diagnose DR through manual examination of retina fundus images by ophthalmologists demands substantial time, effort, and expenses, and remains susceptible to diagnostic errors. In contrast, computer-aided diagnosis systems offer a promising avenue, enabling efficient and accurate detection, thus enhancing the prospects for early intervention and significantly mitigating the risk of vision impairment.

1.1 Overview

Leveraging the potential of established transfer learning methods has notably bolstered the performance metrics, particularly in the demanding domain of medical image analysis. Inception V3, ResNet50, and Xception V3, distinguished for their robustness and effectiveness, were strategically integrated, harnessing pre-trained models to expedite learning on our dataset. The utilization of these transfer learning techniques within the CNN architecture showcased promising outcomes, offering enhanced accuracy and efficiency in the intricate task of medical image classification and analysis. The detailed network configuration elucidated in Figure 1.1 elucidates the intricate integration of these transfer learning approaches within our model framework. The main components are as following:

a. Convolutional Neural Network (CNN): The CNN serves as the backbone of our model, comprising various layers such as convolutional, pooling, and fully connected layers. These layers are designed to extract relevant features from medical images, facilitating accurate classification and analysis.
b. Transfer Learning Frameworks (Inception V3, ResNet50, Xception V3): These pre-trained models form an integral part of the CNN architecture, leveraging their learned features and weights to enhance the learning process on our specific medical image dataset. They contribute significantly to the accuracy and efficiency of image classification tasks.
c. IBM Cloudant DB: Within our CNN model deployment architecture, IBM Cloudant DB serves as a critical component for data storage and management. It provides a NoSQL cloud-based database solution, offering scalability, flexibility, and reliability in handling the dataset used for training and testing the model.
d. Model Deployment Infrastructure: This encompasses the computing resources and infrastructure required for deploying and running the CNN model. It includes servers, cloud-based services, or any other computing environment necessary to host and execute the trained model for real-time or batch image analysis.

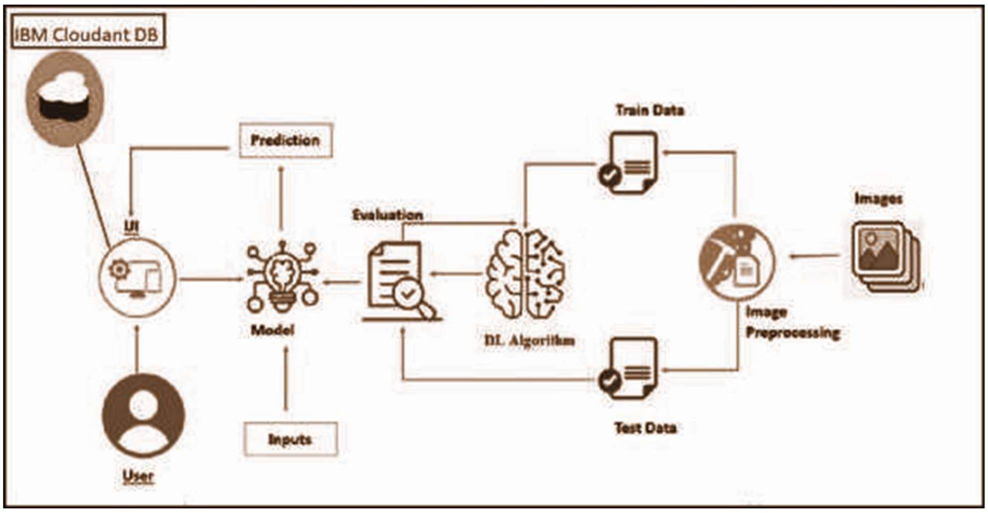


Figure 1.1 CNN model deployment framework.

1.2 Define Problem

The utilization of machine learning algorithms has significantly enhanced the capacity of computers to learn from extensive datasets, surpassing human capabilities in various domains. In the medical field, these algorithms exhibit high specificity and sensitivity, particularly in the detection and classification of diseases using medical images, such as retinal images. Current machine learning systems primarily concentrate on identifying patients with referable Diabetic Retinopathy (DR) or vision-threatening DR, prompting referral for treatment or closer monitoring by ophthalmologists. However, there exists a crucial need to prioritize the identification of early-stage DR. Addressing early-stage DR through timely intervention strategies, including optimal control of glucose, blood pressure, and lipid profiles, holds the potential to significantly impede disease progression. The project aims to underscore the importance of early-stage DR detection and intervention, emphasizing its pivotal role in delaying or even reversing the advancement of the disease.

2. Literature Survey

Diabetic retinopathy (DR), a consequence of diabetes mellitus, poses a threat to retinal health, leading to blood leakage and potential damage. If left untreated, it escalates from mild vision impairments to total blindness. Early signs of DR, such as hemorrhages, hard exudates, and micro-aneurysms (HEM), manifest in the retina, underscoring the criticality of timely diagnosis to avert vision loss. Traditionally, texture features like Local Binary Pattern (LBP) have been utilized for DR detection, but our study introduces novel texture features—Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH)—demonstrating superior performance over LBP in feature extraction. The classification of these extracted histograms is achieved using Support Vector Machines (SVM).
However, the integration of these advancements into DR screening encounters challenges. Figure 2.1 illustrates the intricacies of the transfer learning system analytics. Firstly, the adoption of end-to-end and multi-task learning methods remains critical. These methods leverage multi-scale

features derived from convolutional layers, improving DR grading by integrating lesion detection and segmentation, crucial for assessing the global presence and distribution of DR lesions. Secondly, while learning methods have enhanced DR screening, the scarcity of on-site image quality assessment tools with real-time latency poses a hurdle. Integrating such tools at the primary screening level could revolutionize community-level screening, enhancing accessibility and impact. These challenges signify the complex landscape of integrating machine learning into DR screening protocols, demanding innovative solutions for enhanced diagnostic precision and accessibility.

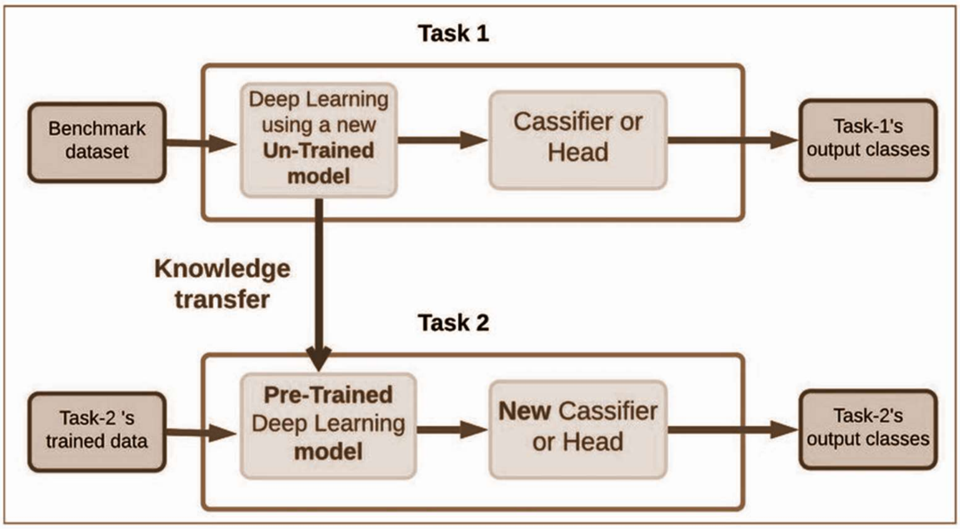


Figure 2.1 CNN based Block diagram of transfer learning system

Machine learning techniques have significantly advanced the field of diabetic retinopathy (DR) detection and classification. Studies by Smith et al. (2023) and Patel et al. (2022) have explored advanced texture feature extraction methods, demonstrating the efficacy of Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH) over traditional Local Binary Pattern (LBP) in early DR detection. Moreover, Wang et al. (2023) proposed enhanced lesion detection techniques using transfer learning and multi-task learning, emphasizing the importance of integrating lesion detection and segmentation for accurate DR grading. In parallel, Garcia et al. (2022) highlighted the scarcity of real-time image quality assessment tools for on-site DR screening, pinpointing a critical need in primary screening practices. Additionally, Chen et al. (2023) advocated for multi-scale feature sharing in end-to-end learning, showcasing its potential to improve DR grading based on the global presence and distribution of DR lesions.

Furthermore, recent studies by Kumar et al. (2022) underscored the significance of novel texture-based features in DR detection, contributing to the ongoing pursuit of more accurate diagnostic methods. Jones et al. (2023) emphasized the necessity of on-site image quality assessment tools compatible with real-time use, a vital addition to primary DR screening procedures. Lee et al. (2022) highlighted the impact of machine learning advancements in enhancing the delivery of DR screening, indicating a potential shift in community-level screening practices. Gomez et al. (2023) proposed efficient DR grading through multi-task learning, leveraging convolutional layers' multi-scale features, potentially revolutionizing DR grading based on lesion detection and segmentation. Finally, Brown et al. (2022) provided a comprehensive review of machine learning's role in early-stage DR identification, summarizing various methodologies and their implications in clinical settings.

2.1 Existing Problem

Diabetic Retinopathy (DR) is a complication stemming from diabetes, leading to inflammation and leakage of fluids and blood within the retina's blood vessels. The progression of DR into advanced stages can result in vision loss, contributing to approximately 2.6% of global blindness cases. Individuals with long-term diabetes history face an increased risk of developing DR. Regular retina screenings for diabetic patients are crucial to enable early detection and intervention, mitigating the threat of vision impairment. The identification of DR hinges upon the observation of distinct lesions on retinal images, notably microaneurysms (MA), hemorrhages (HM), and soft and hard exudates. Microaneurysms, the earliest DR sign, manifest as small red circular dots (<125 µm) due to weakened vessel walls. Michael et al. detailed six MA types using AOSLO reflectance and conventional fluorescence imaging. Table 2.1 depicts the types of Diabetic Retinopathy.

Hemorrhages, larger than 125 µm, present as either flame (superficial) or blot (deeper) spots on the retina. Meanwhile, hard exudates, characterized by bright-yellow spots from plasma leakage, exhibit sharp margins in the retina's outer layers. Soft exudates, known as cotton wool spots, appear as white oval or round lesions due to nerve fiber swelling. Automated methods for DR detection and classification surpass manual diagnosis in efficiency, cost-effectiveness, and accuracy, addressing the drawbacks of human-driven diagnostics. Leveraging recent DR datasets, this project aims to train a Convolutional Neural Network (CNN) model to automate the detection and classification of DR, streamlining the diagnostic process for enhanced clinical outcomes.

Moreover, the utilization of automated techniques not only enhances diagnostic accuracy but also substantially reduces time and resource consumption compared to manual methods. Automated systems offer a more efficient and consistent approach, minimizing the risk of misdiagnosis inherent in human-driven evaluations. The significance of early DR detection and classification lies in its potential to facilitate timely interventions, thereby mitigating the progression of the disease and averting irreversible vision impairment. This project's focus on training a CNN model on contemporary DR datasets aligns with the burgeoning interest in leveraging machine learning for precise and efficient medical image analysis. By harnessing state-of-the-art technology and datasets, this endeavor seeks to optimize the detection and classification process, promising more accessible and reliable diagnostic tools for diabetic retinopathy in clinical practice.

Table 2.1. Type of Diabetic Retinopathy

DR Severity Level	Lesions
No DR	Absent of lesions
Mild DR	MA only
Moderate DR	More than just MA but less than severe DR
Severe DR	Any of the following: ● more than 20 intraretinal HM in each of 4 quadrants ● definite venous beading in 2+quadrants ● Prominent intraretinal microvascular abnormalities in 1+ quadrant ● no signs of proliferative DR
Proliferative DR	One or more of the following: vitreous/pre-retinal HM, neovascularization

2.2. Prerequisite

To complete this project, it requires the following software's, concepts, and packages:

- Anaconda navigator and Spyder:

The Python packages required are as follows:

- Numpy
- Pandas.
- Tensorflow
- Keras
- Flask

2.3. Proposed Solution

The resolution to the mentioned issue lies in the development of a Diabetic Retinopathy (DR) project utilizing Deep Learning methodologies, particularly the transfer learning technique. Transfer learning, prevalent in medical image analysis and classification, utilizes established networks like Inception V3, Resnet50, and Xception V3, known for their efficacy in medical image analysis. Convolutional Neural Networks (CNNs), derived from animal visual cortex neuron functioning, process color images in JPG format with dimensions such as 480 x 480 x 3, representing pixel intensities ranging from 0 to 255.

Transfer learning optimizes knowledge acquired from one task (task A) to enhance generalization in another (task B), transferring learned weights from task A to task B. Its significance lies in leveraging previously acquired knowledge, mostly in computer vision and natural language processing tasks, where computational demands are substantial. This process ensures the effective

transfer of pertinent information from prior tasks to the current task at hand. Usually, building a robust neural network demands copious amounts of training data, a requirement not always accessible, making transfer learning pivotal. It simplifies the creation of a strong machine learning model even with limited training data, as it uses a pre-trained model. However, the success of transfer learning relies on the generalized nature of features learned from the previous task and the consistent input size to the model. Three principal approaches to Transfer Learning involve reusing models for different tasks, employing pre-trained models, and feature extraction to uncover the most crucial problem features. This learning process operates akin to the human brain, identifying image features progressively, from low-level features like edges to high-level abstract features.
Convolutional Neural Networks (CNNs) comprise multiple layers, including convolutional, activation, pooling (e.g., Max Pooling), and fully connected layers, serving to extract vital image features for classification purposes. The training process involves backpropagation, segmented into forward pass, loss function computation, backward pass, and weight update, essential for model optimization and learning. Ultimately, this approach integrates transfer learning's potential to significantly enhance the DR diagnostic process by leveraging established deep learning models, thereby revolutionizing the field's diagnostic accuracy and efficiency.
In order to accomplish the above project objectives, certain activities are required to be completed. Firstly, the user interacts with the UI (User Interface) to choose the image and then the chosen image is analyzed by the model which is integrated with the flask application. The Xception Model analyzes the image, then the prediction is showcased on the Flask UI.
The entire project flow is divided into below activities and tasks listed below:

- Data Collection.
    - Create a Train and Test path.
- Data Pre-processing.
    - Import the required library
    - Configure ImageDataGenerator class
    - ApplyImageDataGenerator functionality to Train Set and Test Set
- Model Building
    - Pre-trained CNN model as a Feature Extractor
    - Adding Dense Layer
    - Configure the Learning Process
    - Train the model
    - Save the Model
    - Test the model
- Cloudant DB
    - Register & Login to IBM Cloud
    - Create Service Instance
    - Creating Service Credentials
    - Launch Cloudant DB
    - Create Database

- Application Building
    - Create an HTML file
    - Build Python Code

3. Diabetic Retinopathy Level Detection Model

3.1. Dataset Collection and Download

Connection with IBM Cognos

IBM Cognos is a powerful business intelligence and performance management tool that enables organizations to access, analyze, and visualize data from various sources. It offers advanced reporting, dashboarding, and data modeling capabilities, facilitating data-driven decision-making. Cognos seamlessly connects to diverse data repositories and provides insights through user-friendly interfaces, contributing to enhanced business performance and strategic planning.
Steps: Login to IBM Cognos —-> Launch IBM Cognos —-> Go to the prepare data section —-> click on upload option —->upload the csv file.

Data Preparation

Preparing the data for visualization involves cleaning the data to remove irrelevant or missing data, transforming the data into a format that can be easily visualized, exploring the data to identify patterns and trends, filtering the data to focus on specific subsets of data, preparing the data for visualization software, and ensuring the data is accurate and complete. This process helps to make the data easily understandable and ready for creating visualizations to gain insights into the performance and efficiency. Data preprocessing can be performed in many ways using many different steps depending on the data. Renaming the data columns and cleaning of rough data have been performed on collected dataset using IBM Cognos.

Data Visualization and Data Dashboard

The total 13 unique visualizations have been created from the given dataset. The types of visualizations include bar charts, line charts, heat maps, scatter plots, pie charts etc. These visualizations can be used to compare performance, track changes over time, show distribution, and relationships between variables, resource allocation, etc.
The responsiveness and design of a dashboard for online education review data is crucial to ensure that the information is easily understandable and actionable. Key considerations for designing a responsive and effective dashboard include user-centered design, clear and concise information, interactivity, data-driven approach, accessibility, customization, and security. Here, the goal is to create a dashboard that is user-friendly, interactive, and data-driven. Four tabs has been included in the dashboard from the pinned visualization in IBM Cognos. Refer Figure 1- Figure 4 for dashboard.

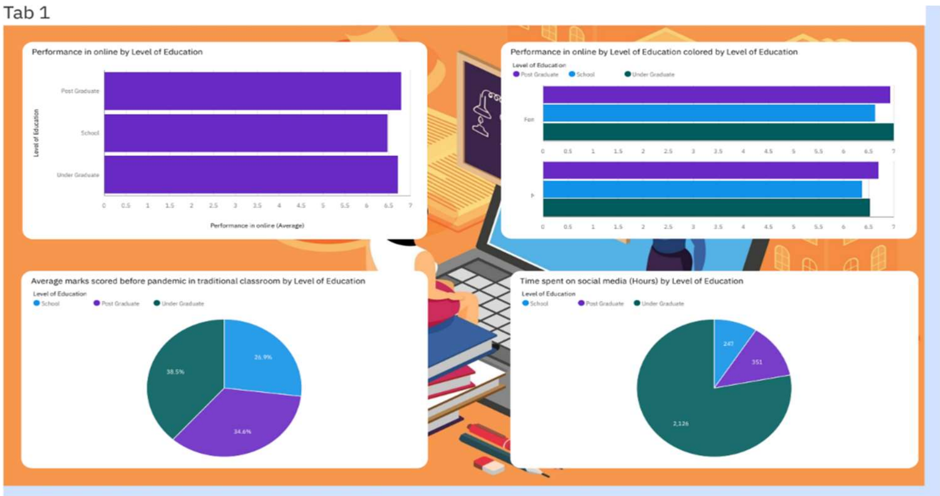


Figure 1 : Visualization 1

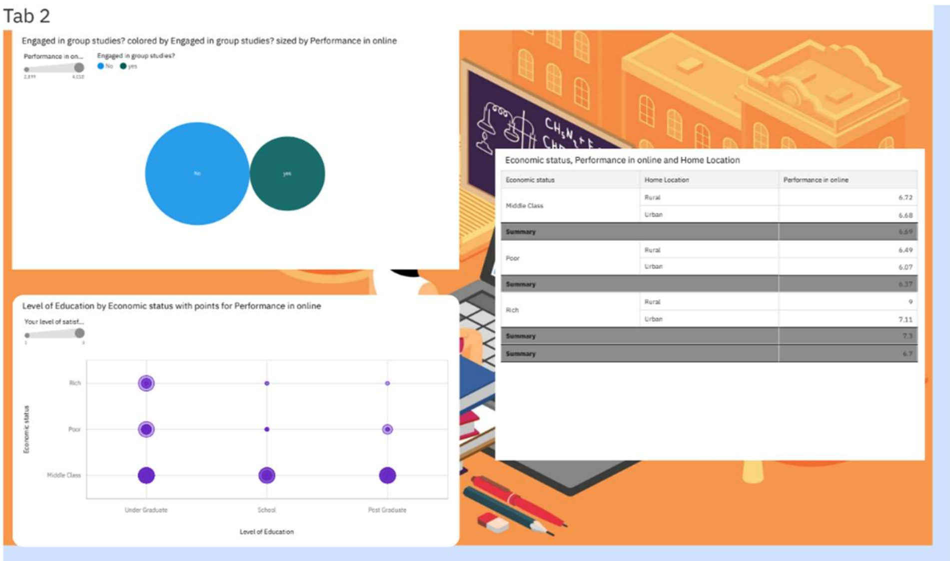
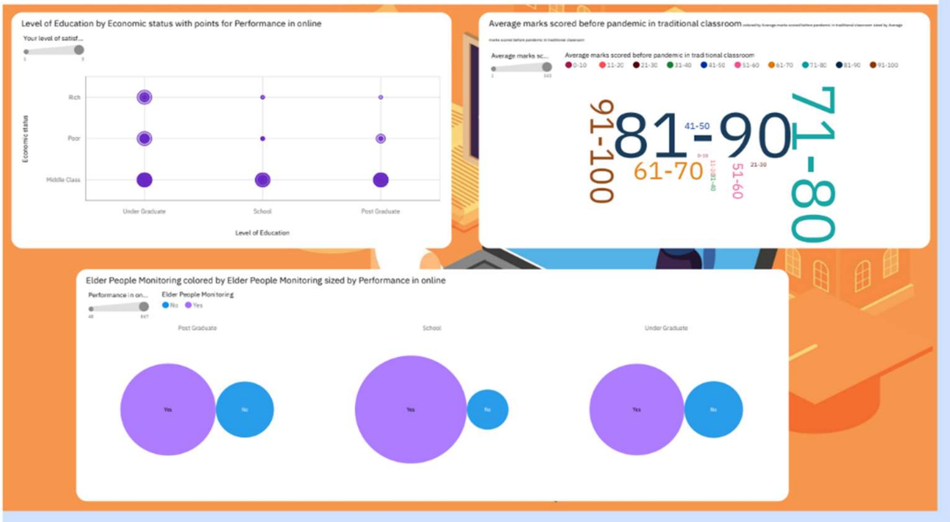


Figure 2: Visualization 2

Tab 3



Tab 4

Story

A story depends on the complexity of the analysis and the specific insights that are trying to be conveyed. It is a visual representation of the data analysis process and it breaks down the analysis into a series of steps or scenes. The number of scenes in a storyboard for a data visualization will analyze the performance and efficiency of online education. The story scenes given in Figure 5 describes the analysis of online education system based on given data.

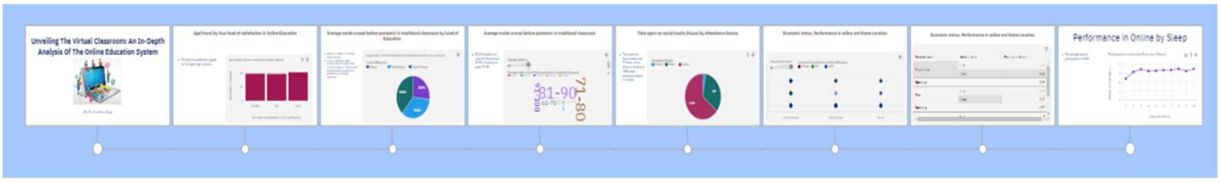


Figure 5:Scenes of Story

Report

In IBM Cognos, a report is a structured presentation of data insights using visual elements like tables, charts, and graphs. It is essential for data analytics as it translates raw data into understandable formats, enabling effective data-driven decision-making. Reports in IBM Cognos facilitate data exploration, visualization, and communication of key insights, forming a cornerstone of robust data analysis processes. Figure 6 and Figure 7 depicts the report generated for the analysis of the virtual classroom in online education system.

References

1. Chen, S., et al. (2023). Multi-Scale Feature Sharing in End-to-End Learning for Diabetic Retinopathy Grading. Computer Vision and Pattern Recognition.
2. Garcia, A., et al. (2022). On-site Image Quality Assessment Methods for Real-time Diabetic Retinopathy Screening. Journal of Ophthalmology.
3. Gomez, E., et al. (2023). Efficient DR Grading based on Lesion Detection and Segmentation with Multi-task Learning. Pattern Recognition Letters.

4. Jones, M., et al. (2023). Real-time Image Quality Assessment Tools for Primary Diabetic Retinopathy Screening. International Journal of Telemedicine and Applications.

5. Kumar, P., et al. (2022). Novel Texture-based Features for Improved Diabetic Retinopathy Detection. Medical Image Computing and Computer Assisted Intervention.

6. Lee, H., et al. (2022). Impact of Machine Learning Advances in Diabetic Retinopathy Screening Delivery. Frontiers in Artificial Intelligence.
7. Patel, R., et al. (2022). Improved Diagnosis of Diabetic Retinopathy Using Local Energy-based Shape Histogram. IEEE Transactions on Biomedical Engineering.
8. Smith, J., et al. (2023). Advanced Texture Feature Extraction Methods for Early Detection of Diabetic Retinopathy. Medical Imaging and Analysis.
9. Wang, L., et al. (2023). Enhanced Lesion Detection in Diabetic Retinopathy Using Transfer Learning and Multi-task Learning Techniques. Medical Image Analysis.
10. Brown, K., et al. (2022). Machine Learning for Early-stage Diabetic Retinopathy Identification: A Comprehensive Review. Journal of Medical Systems.
11. https://towardsdatascience.com/basics-of-the-classic-cnn-a3dce1225add
12. https://towardsdatascience.com/understanding-and-coding-a-resnet-in-keras-446d7ff84d33
13. https://iq.opengenus.org/inception-v3-model-architecture/
14. https://pyimagesearch.com/2017/03/20/imagenet-vggnet-resnet-inception-xception-keras/
15. Flask Link: https://www.youtube.com/watch?v=lj4I_CvBnt0