Identification and Classification of Diabetic Retinopathy

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Certificate of Approval

This is to certify that Ayush Singh, Aryan Shaw, Mayukh Sen, and Agni Sain have completed the project work entitled **"Identification and Classification of Diabetic Retinopathy"** under my supervision. This project work is submitted fulfilling the norms of academic standard for B. Tech Degree in Electronics and Communication Engineering of the Maulana Kalam Azad University of Technology.

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This is to declare that this report has been written by us. All information included from other sources has been duly acknowledged. This work has not been submitted or published anywhere for any degree whatsoever. We aver that if any part of the report is found to be plagiarized, we shall take full responsibility for it.

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Abstract

Diabetic retinopathy (DR) is a severe eye disease that affects individuals with diabetes, leading to vision loss or even blindness if left untreated. Early detection and classification of DR is crucial for timely intervention and treatment. In this project, we propose a methodology for the identification and classification of diabetic retinopathy using Convolutional Neural Networks (CNN) and three popular CNN architectures: MobileNet2, EfficientNet, and Inception. We evaluate the performance of these models on a large dataset of retinal images and compare their accuracy, precision, recall, and F1-score. Our results demonstrate the effectiveness of CNN-based models in accurately identifying and classifying diabetic retinopathy, providing a potential solution for early diagnosis and treatment.

Diabetic retinopathy poses a significant global health challenge, impacting millions of individuals with diabetes. Timely detection and appropriate management are vital for preventing irreversible vision loss. Recent advances in deep learning and computer vision have shown promising results in medical image analysis. This project seeks to leverage the power of CNNs and explore the performance of different CNN architectures to aid in the identification and classification of diabetic retinopathy. Developing accurate and efficient models can assist healthcare professionals in diagnosing and managing this debilitating eye disease more effectively.

Introduction

What is Diabetic Retinopathy?

Diabetic retinopathy is a progressive eye disease caused by prolonged exposure to high blood sugar levels in individuals with diabetes. It damages the blood vessels in the retina, leading to vision impairment. Diabetic retinopathy can progress through various stages, including mild non-proliferative retinopathy, moderate non-proliferative retinopathy, severe non-proliferative retinopathy, and proliferative retinopathy. Early detection and intervention are crucial for preventing disease progression and preserving vision. This project focuses on developing a robust methodology for identifying and classifying diabetic retinopathy using CNN-based models.

What are the types of Diabetic Retinopathy?

Diabetic retinopathy is categorized into two main types:

- **Non-proliferative diabetic retinopathy (NPDR):** Non-proliferative diabetic retinopathy (NPDR) is the early stage characterized by microaneurysms, retinal haemorrhages, and the formation of hard exudates.
- **Proliferative diabetic retinopathy (PDR):** Proliferative diabetic retinopathy (PDR) is the advanced stage marked by the growth of abnormal blood vessels in the retina, which can cause retinal detachment and severe vision loss.

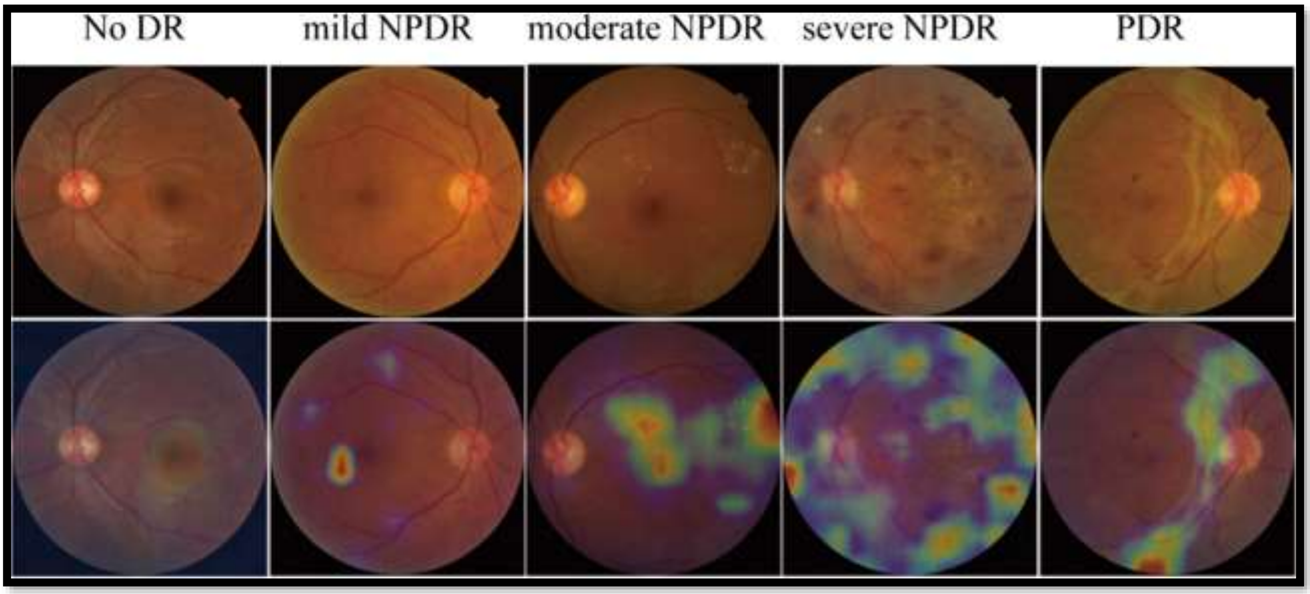
ICDR Classification of Diabetic Retinopathy.

The International Clinic Diabetic Retinopathy (ICDR) classification was published in 2003 after a consensus of 31 retina specialists, endocrinologists, and epidemiologists from 16 countries and sponsored by the American Academy of Ophthalmology. The ICDR classified DR on a five-stage severity scale and classified diabetic macular edema as apparently absent or present.

ICDR is applied in the EYEPACS dataset, Asian Pacific Tele-Ophthalmology Society dataset, Indian Diabetic Retinopathy Image Dataset, Messidor 1 and 2 datasets which have been consulted for our project.

The types are: -

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



Symptoms of Diabetic Retinopathy

Symptoms of diabetic retinopathy include blurred or distorted vision difficulty seeing at night, and the presence of floaters or dark spots in the visual field. Regular eye examinations, including fundus photography or optical coherence tomography, are essential for diagnosing and monitoring the disease's progression.

Prevention of Diabetic Retinopathy

One can reduce your risk of developing diabetic retinopathy, or help stop it getting worse, by keeping your blood sugar levels, blood pressure and cholesterol levels under control.

This can often be done by making healthy lifestyle choices, although some people will also need to take medication.

Early detection of retinopathy increases the chances of treatment being effective and stopping it getting worse. A precautionary check should be done if you develop any of these symptoms: -

- gradually worsening vision
- sudden vision loss
- shapes floating in your field of vision.
- blurred vision
- eye pain or redness
- difficulty seeing in the dark

These symptoms do not necessarily mean you have diabetic retinopathy, but it's important to get them checked out straight away.

Project Objective

The US Center for Disease Control and Prevention estimates that 29.1 million people in the US have diabetes and the World Health Organization estimates that 347 million people have the disease worldwide. Diabetic Retinopathy (DR) is an eye disease associated with long-standing diabetes. Recent advances in deep learning and computer vision have shown promising results in medical image analysis.

Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital colour fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.

Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is effective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed. As the number of individuals with diabetes continues to grow, the infrastructure needed to prevent blindness due to DR will become even more insufficient.

The aim of our project is to develop a software solution to process fundus images and detect Diabetic Retinopathy. This project seeks to leverage the power of CNNs and explore the performance of different CNN architectures to aid in the identification and classification of diabetic retinopathy. Developing accurate and efficient models can assist healthcare professionals in diagnosing and managing this debilitating eye disease more effectively. 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.For better understanding and user experience, we will deploy the model on a web application.

Literature study

1. **Gulshan, V., Peng, L., Coram, M., Stumpe, M.C., Wu, D., Narayanaswamy, A., ... & Raman, R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402-2410.**
    - This study demonstrates the effectiveness of CNNs in diabetic retinopathy detection and serves as a foundation for subsequent research in the field.
2. **Ting, D.S.W., Cheung, C.Y., Lim, G., Tan, G.S.W., Quang, N.D., Gan, A., ... & Wong, T.Y. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multi-ethnic populations with diabetes. JAMA, 318(22), 2211-2223.**
    - This research focuses on the development of a deep learning system for diabetic retinopathy detection and classification, providing insights into the potential of CNNs in handling multi-ethnic populations.
3. **Rajan, D., & Subramanian, S. (2018). A comprehensive review of diabetic retinopathy detection, prediction, and classification using machine learning techniques. Journal of Healthcare Engineering, 2018.**
    - This review paper provides an overview of various machine learning techniques, including CNNs, applied to diabetic retinopathy detection and classification, highlighting their strengths and limitations.

4. **O'Donoghue, G., McNally, S., & Ní Dhubhghaill, S. (2018). Machine learning, image recognition, and the future of ophthalmology. Expert Review of Ophthalmology, 13(3), 141-143.**

   - This review article discusses the potential of machine learning, particularly CNNs, in revolutionizing the field of ophthalmology, including the detection and classification of diabetic retinopathy.

5. **Srinivasan, P.P., Kim, L.A., Mettu, P.S., Cousins, S.W., Comer, G.M., & Izatt, J.A. (2018). Fully automated detection of diabetic macular edema and dry age-related macular degeneration from optical coherence tomography images. Biomedical Optics Express, 9(12), 6200-6211**.

   - This study focuses on the application of CNNs for the detection of diabetic macular edema, a common complication of diabetic retinopathy, using optical coherence tomography images, demonstrating the versatility of CNNs in different imaging modalities.

6. **Tan, J.H., Acharya, U.R., Bhandary, S.V., Chokkadi, S., Sree, S.V., & Martis, R.J. (2018). Automated diagnosis of diabetic retinopathy stages using digital fundus images. Biocybernetics and Biomedical Engineering, 38(1), 259-269**.

   - This research explores the use of CNNs for the automated diagnosis of different stages of diabetic retinopathy, providing insights into the potential of CNNs for precise classification.

These studies provide a solid foundation for the project and demonstrate the effectiveness of CNNs, as well as the specific architectures like MobileNet2, Efficient Net in diabetic retinopathy identification and classification tasks. They highlight the potential of deep learning algorithms in enhancing the accuracy and efficiency.

Methodology

The Data

The data originates from a 2015 Kaggle competition sponsored by the California Healthcare Foundation. However, is an atypical Kaggle dataset. In most Kaggle competitions, the data has already been cleaned, giving the data scientist very little to pre-process. 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 pre-processing section, this data is extremely noisy, and requires multiple pre-processing 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 pre-processing. It consists of large set of high-resolution retina images taken under a variety of imaging conditions. A left and right field is provided for every subject. Images are labelled with a subject id as well as either left or right (e.g., 1_left.jpeg is the left eye of patient id 1).

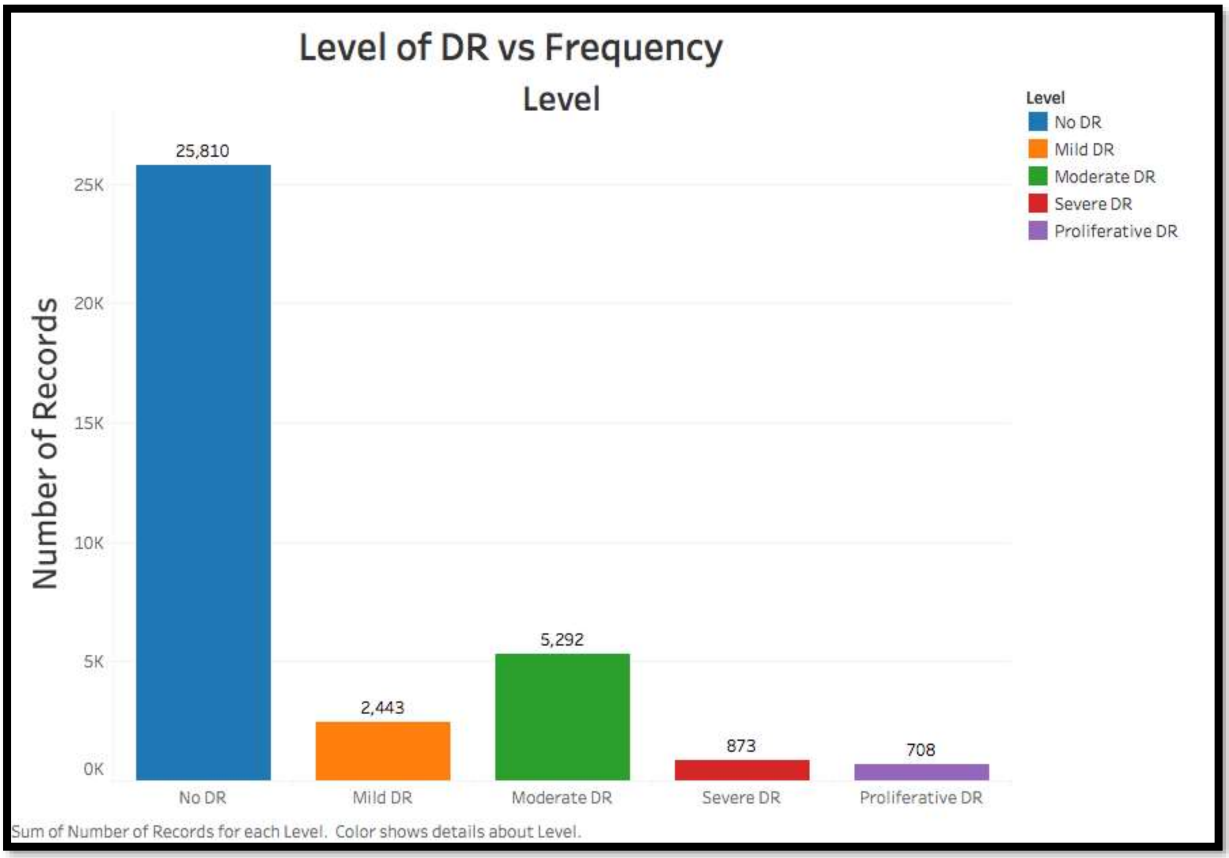
A clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:

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

The images in the dataset come from different models and types of cameras. Database contains noise in both the images and labels. Images may contain artifacts, be out of focus, underexposed, or overexposed. Our aim is to develop robust algorithms that can function in the presence of noise and variation.

Exploratory Data Analysis

The very first item analysed was the training labels. While there are five categories to predict against, the plot below shows the severe class imbalance in the original dataset.

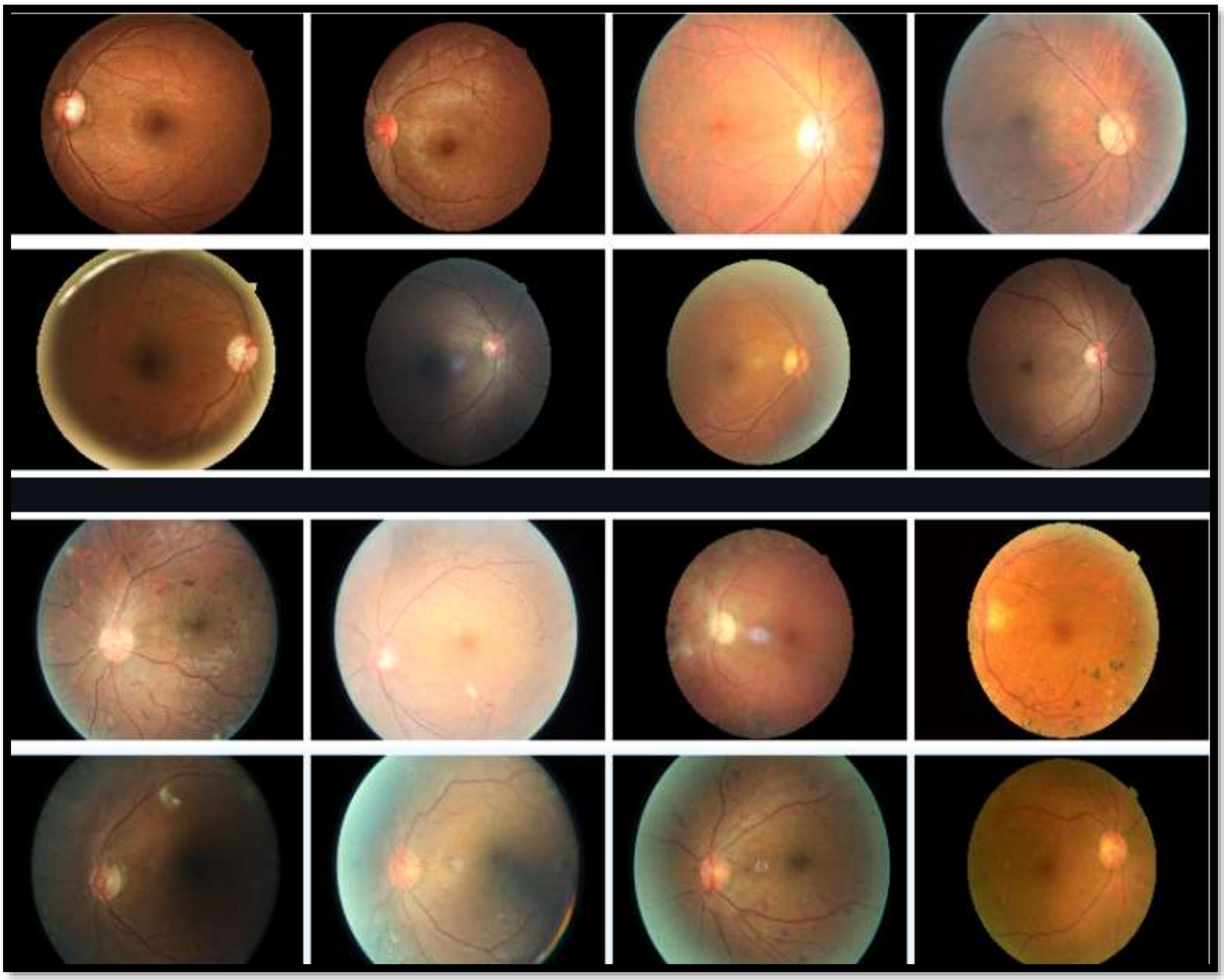


Of the original training data, 25,810 images are classified as not having retinopathy, while 9,316 are classified as having retinopathy.

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

Furthermore, the variance between images of the eyes is extremely high.

Sample Fundus Images From Dataset



The first two rows of images show class 0 (no retinopathy); the second two rows show class 4 (proliferative retinopathy).

Exploratory Data Analysis Will be followed by image pre-processing.

Image Pre-processing

Image pre-processing plays a crucial role in improving the quality and consistency of input data for diabetic retinopathy classification using CNNs.

The pre-processing pipeline is the following:

- Download all images.
- Crop & resize all images using the resizing script and the pre-processing script.
- Rotate & mirror all images using the rotation script.
- Convert all images to array of NumPy arrays, using the conversion script.

Image Resizing: Resizing the input images to a standardized resolution is essential to ensure consistency and compatibility across the dataset. It involves resizing all images to a specific size which is commonly used in CNN architectures like MobileNet2, EfficientNet etc Resizing ensures that the models can process the images efficiently and reduces computational complexity.

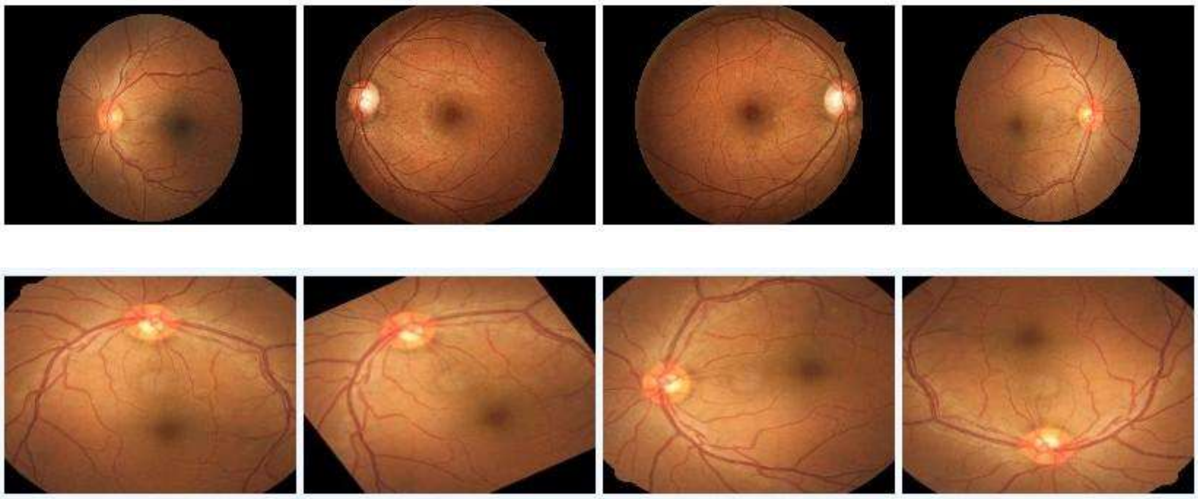
All images were scaled down to 256 by 256. Despite taking longer to train, the detail present in photos of this size is much greater than at 128 by 128.

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

Normalization: Normalizing the pixel values of the images is necessary to bring them to a consistent scale and facilitate better convergence during model training. This step involves transforming the pixel values from their original range (e.g., 0-255 for 8-bit grayscale or RGB images) to a normalized range, typically between 0 and 1. Normalization helps in mitigating the impact of varying illumination conditions and improves the stability of the training process.

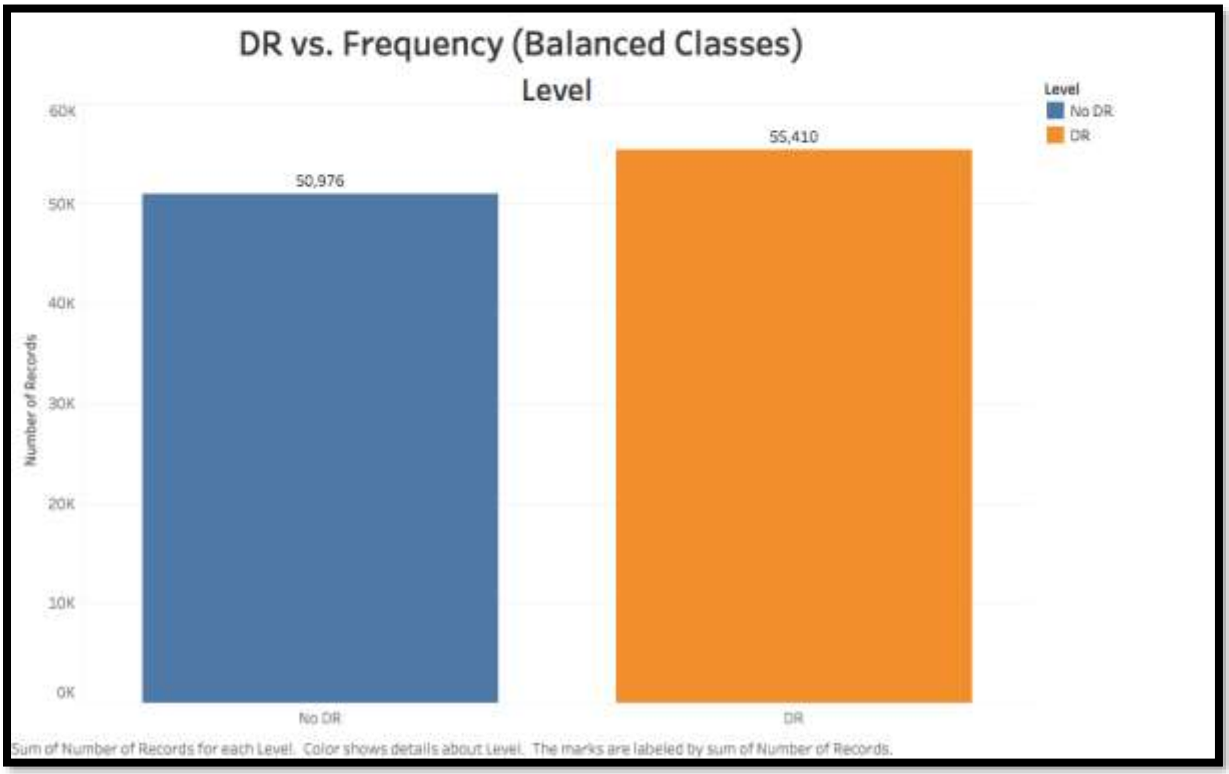
Data Augmentation: Data augmentation techniques can be employed to increase the diversity and variability of the training data. These techniques involve applying random transformations to the images, such as rotation, scaling, flipping, and shifting. By generating new augmented images, the dataset's size is effectively increased, which helps prevent overfitting and improves the generalization capability of the models. Data augmentation is particularly useful when the available dataset is limited.

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. 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.

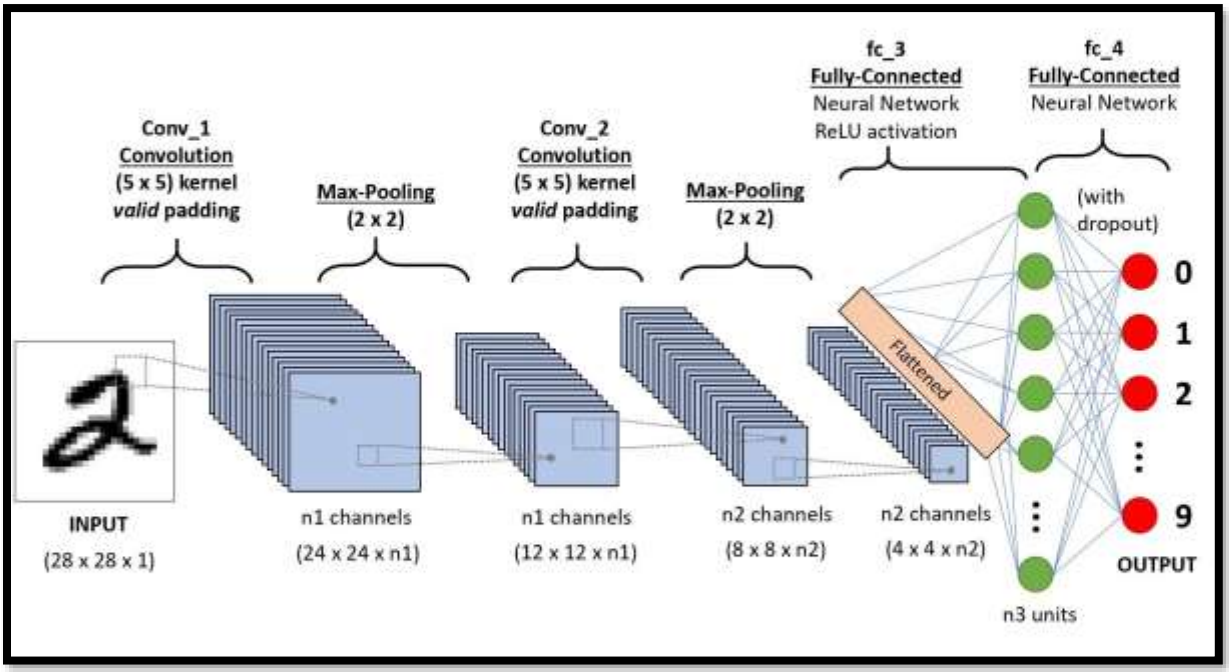
It is important to note that the specific preprocessing techniques employed may vary depending on the characteristics of the dataset and the requirements of the CNN architectures used. The goal of image pre-processing is to standardize and enhance the quality of the input data, ultimately improving the performance and accuracy of the diabetic retinopathy classification models.



Convolutional Neural Networks

This project utilizes CNN-based models for the identification and classification of diabetic retinopathy. CNNs are a class of deep neural networks that excel in extracting complex features from images, making them well-suited for image classification tasks. Popular CNN architectures, MobileNet and EfficientNet are employed to train the models.

CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract features by applying filters to input images. Pooling layers reduce spatial dimensions, downsampling the feature maps. Fully connected layers provide the final classification based on the extracted features. MobileNet, EfficientNet, and Inception are renowned CNN architectures known for their efficiency and performance in image classification tasks.



The above pictures shows the working mechanism of a CNN.

To train the models, a large dataset of retinal images, comprising both normal and diabetic retinopathy cases, was collected. The images were pre-processed by resizing them to a standardized resolution and normalizing pixel values. The dataset was divided into training, validation, and testing sets.

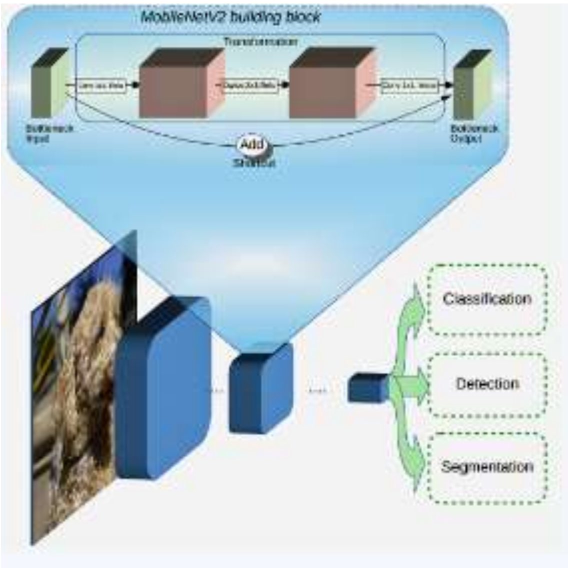
Transfer learning was employed by initializing the CNN architectures with pre-trained weights, originally trained on.

Transfer learning (TL) is a research problem in machine learning (ML) that focuses on applying knowledge gained while solving one task to a related task. For example, knowledge gained while learning to recognize cars could be applied when trying to recognize trucks.

MobileNet

MobileNet is a widely used CNN architecture designed specifically for mobile and embedded devices with limited computational resources. It achieves efficiency by utilizing depth-wise separable convolutions. In traditional convolutions, each input channel is convolved with a different filter, resulting in a high computational cost. However, in depth-wise separable convolutions, the input channels are convolved independently with separate filters, significantly reducing the number of computations. This architecture strikes a balance between model size and accuracy, making it suitable for real-time applications on resource-constrained devices.

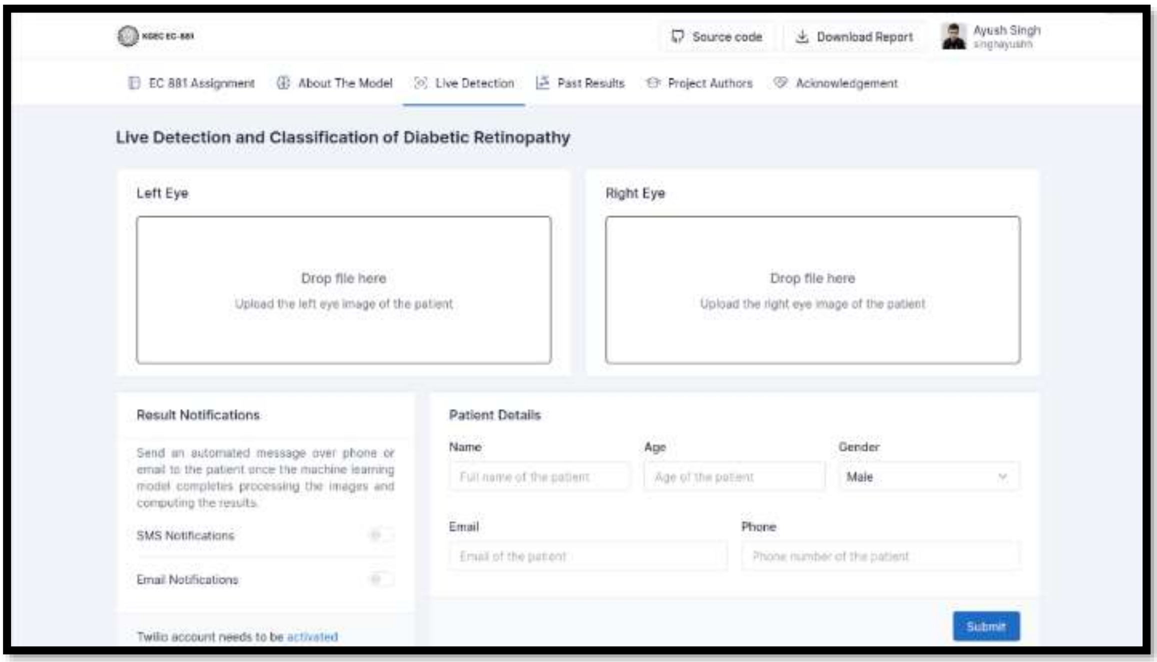
For Our Project we are using MobileNetV2, a stronger version of MobileNet.



The main goal in creating this network is to keep costs and complexity low, making it easy to use for detection and classification on mobile devices or other devices with constrained resources like memory and energy. Low energy consumption models can benefit medical devices and resource-constrained developing nations.

Our Web Application

This section presents a detailed overview of a web application developed using Node.js with TypeScript and the Express framework. The application utilizes MongoDB as the database system and incorporates EJS as the template engine. Additionally, it employs the Child Process library to execute a machine learning script. The purpose of this application is to provide a proof of concept for mimicking diabetic retinopathy detection and classification. Medical staff can register, use the application to upload left and right eye fundus images of patients, and generate machine learning predictions based on these images.



We have developed a web application that interacts with our machine learning model to allow real-time classification of fundus images and mimic the actual usage of the system in medical institutes.

The tech stack used is:

- **Backend code**: NodeTS & Express framework
- **Database**: MongoDB and Redis
- **Front end code**: EJS, CSS, JavaScript

Application Architecture

The application is built on the Node.js runtime environment, which allows server-side JavaScript execution. TypeScript, a typed superset of JavaScript, is used to enhance the development experience by providing static typing. The Express framework is employed to create the server and handle HTTP requests and responses. This framework enables efficient routing and middleware integration. Here's a detailed application architecture for the diabetic retinopathy detection and classification project:

1. Frontend:

- The frontend of the application is built using HTML, CSS, and JavaScript.
- It incorporates the EJS (Embedded JavaScript) template engine to generate dynamic HTML pages.
- The user interface allows medical staff to register, log in, and perform various actions.
- Actions include uploading left and right eye fundus images of patients and viewing prediction results.

2. Backend:

- The backend of the application is developed using Node.js with TypeScript and the Express framework.
- Express provides a robust foundation for creating the server, handling HTTP requests, and managing routes.
- TypeScript adds static typing to enhance code reliability and maintainability.

3. Server:

- The server component listens for incoming HTTP requests from the frontend.
- It utilizes Express to route requests to the appropriate endpoints and execute the corresponding logic.

4. Database:

- MongoDB is used as the database system for storing application data.
- The database schema includes two collections: "users" and "predictions".
- The "users" collection stores information about medical staff, such as their credentials and other relevant details.
- The "predictions" collection is responsible for storing predictions made by users and their corresponding results.

5. User Authentication:

- The application incorporates user authentication to ensure secure access to the system.
- When medical staff register, their credentials are stored securely in the "users" collection.
- During login, the application verifies the provided credentials against the stored values.

6. Image Upload and Processing:

- The frontend allows medical staff to upload left and right eye fundus images of patients.
- Upon upload, the images are sent to the backend as HTTP requests.
- The backend receives the image files and stores them temporarily or permanently, depending on the specific implementation requirements.

7. Machine Learning Integration:

- A separate machine learning script is integrated into the application to perform the diabetic retinopathy prediction.
- The Child Process library in Node.js is utilized to execute the machine learning script as a separate child process.
- The machine learning script takes the uploaded fundus images as input and generates predictions based on its trained models.
- The predictions, along with relevant details such as patient information and results, are stored in the "predictions" collection in the MongoDB database.

8. Response Generation:

- Once the predictions are generated by the machine learning script, the backend constructs the response to be sent back to the frontend.
- The response may include prediction results, patient information, and any other relevant data.
- The EJS template engine is used to generate dynamic HTML pages, incorporating the response data into the appropriate placeholders within the templates.

9. Communication between Components:

- The frontend communicates with the backend through HTTP requests and responses, using RESTful API endpoints.
- The backend interacts with the MongoDB database to store and retrieve data.
- The machine learning script is executed as a separate child process, communicating with the backend through input and output channels.

10. Error Handling and Logging:

- The application incorporates error handling mechanisms to gracefully handle exceptions and errors that may occur during execution.
- Logging functionalities can be implemented to record important events, errors, and diagnostic information for troubleshooting and monitoring purposes.

User Workflow:

Here's a detailed user workflow story for the diabetic retinopathy detection and classification application:

1. Registration: Medical staff members access the application's web interface and navigate to the registration page. They provide their desired username, password, full name, and email address. After submitting the registration form, the application validates the provided information. If successful, the user is registered, and their credentials are securely stored in the database.

2. Login: Registered medical staff members proceed to the login page. They enter their username and password and submit the login form. The application verifies the credentials against the stored values in the database. Upon successful authentication, the user is granted access to the application's main features.

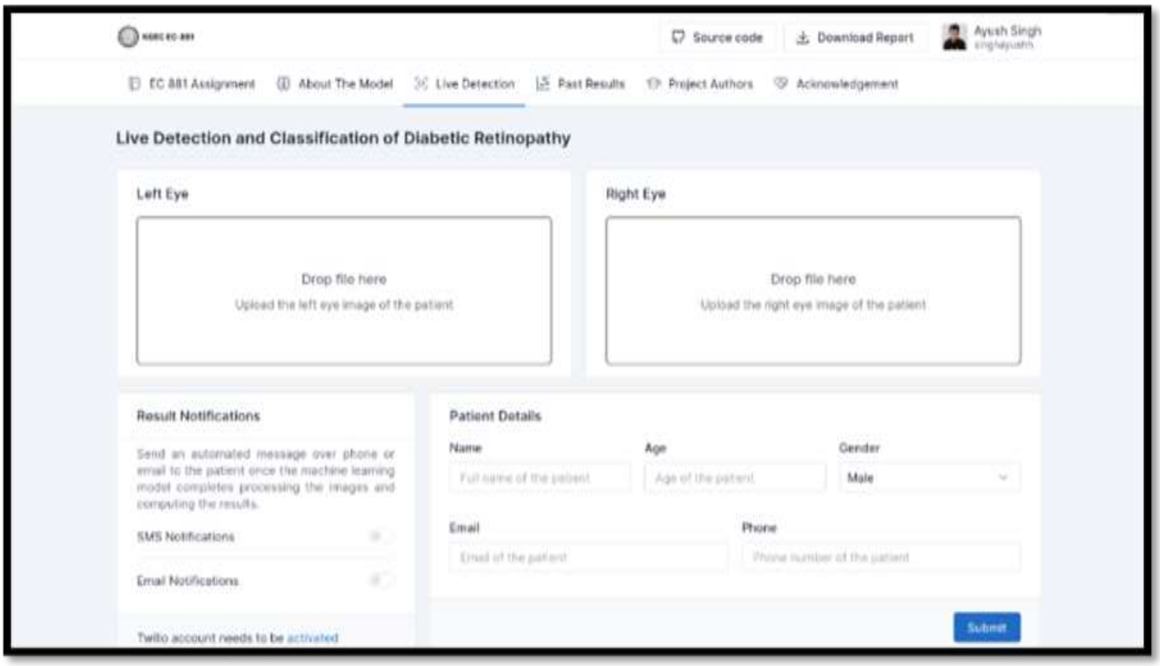
3. Uploading Fundus Images: After logging in, medical staff members are presented with the option to upload left and right eye fundus images of patients. They select the patient for whom the images are being uploaded and choose the corresponding fundus images from their local device. Upon submission, the frontend sends the images as HTTP requests to the backend.

4. Prediction Generation: The backend receives the uploaded fundus images and triggers the machine learning script as a separate child process. The machine learning script processes the images, generates predictions for diabetic retinopathy, and returns the results to the backend. The backend stores the predictions and associated details, including patient and prediction timestamps, in the database's prediction collection.

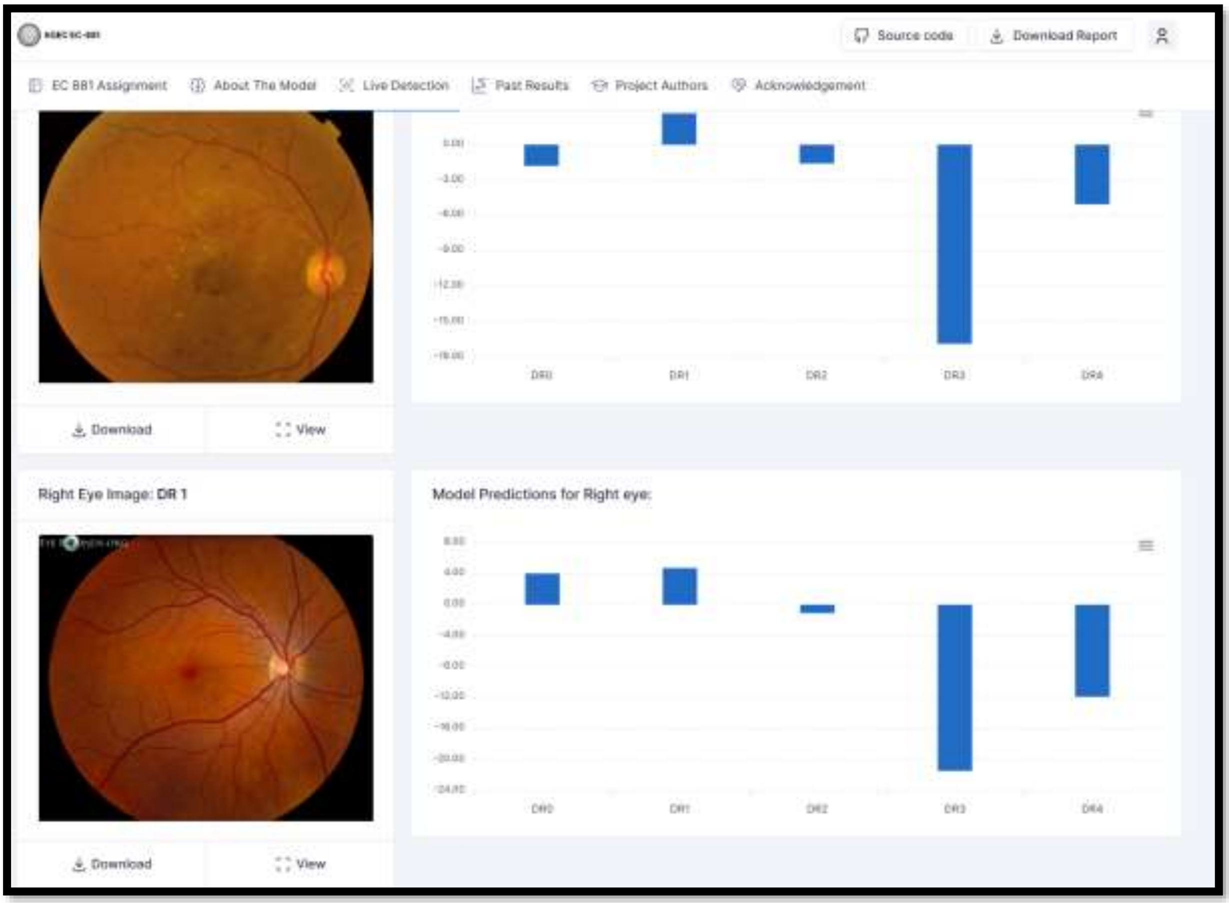
5. Viewing Prediction Results: Medical staff members can view the prediction results for a specific patient. They navigate to the patient's profile or prediction history page and select the desired patient. The application queries the database for predictions associated with the selected patient and retrieves the relevant details. The frontend then dynamically generates a page displaying the patient's prediction results, including the predicted diagnosis or classification and the corresponding timestamps.

6. Iterative Workflow: Medical staff members can repeat the process by uploading additional fundus images for different patients. They can also update patient records or view predictions made by other staff members. The application provides a seamless user experience, allowing medical staff to perform multiple iterations of image upload, prediction generation, and result viewing as needed.

Throughout this user workflow, the application ensures secure authentication, reliable storage of user and prediction data, seamless integration with the machine learning script, and dynamic rendering of prediction results. It empowers medical staff to efficiently upload fundus images, generate predictions, and access the relevant information needed for diabetic retinopathy detection and classification.



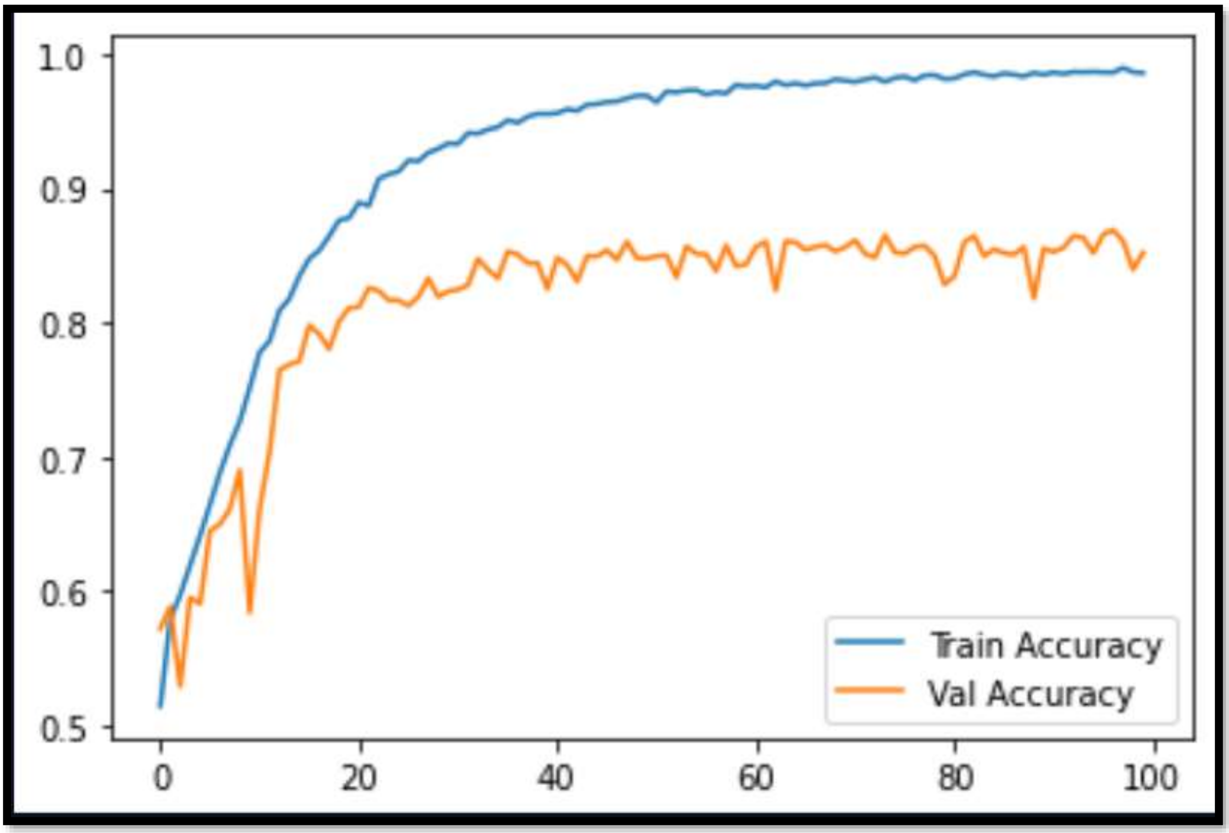
Users can input fundus images with patient details

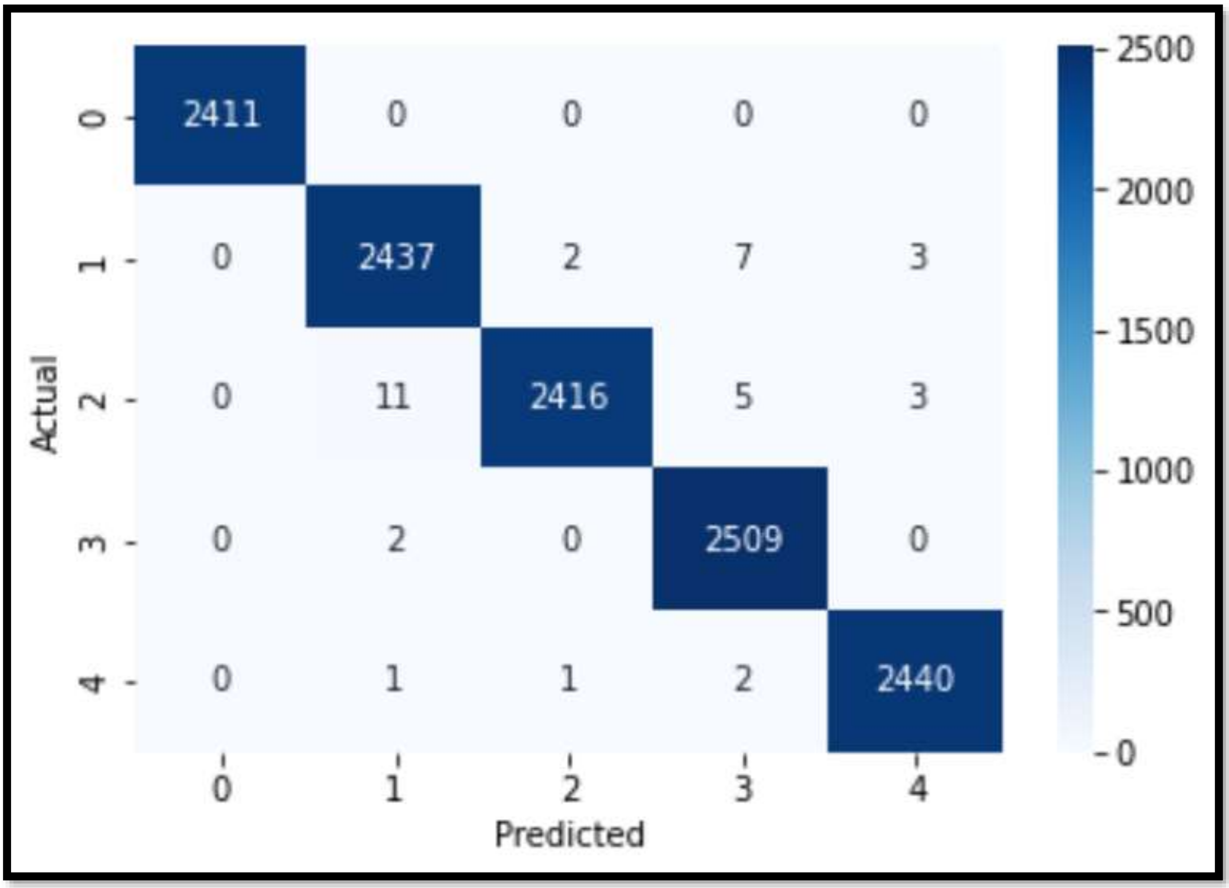


Our application predicting DR1(Mild Diabetic Retinopathy) based on input images.

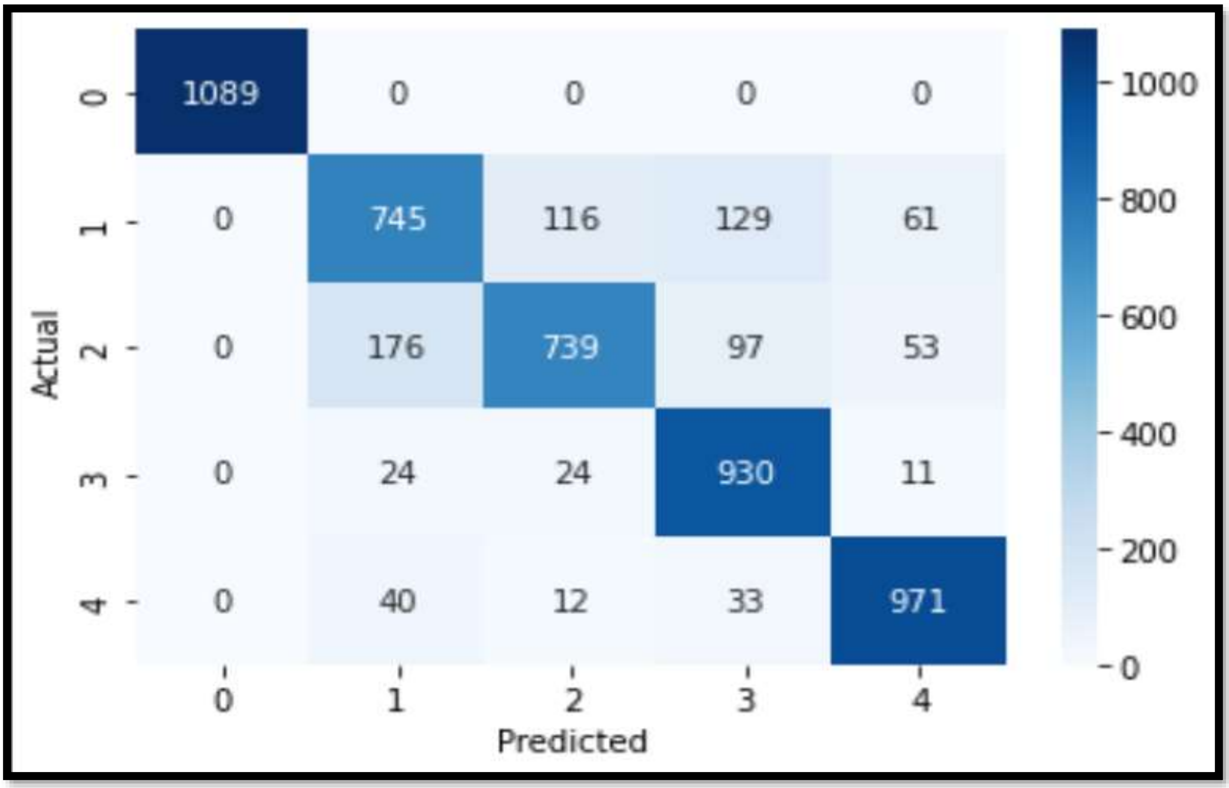
Results

We found that the training accuracy is 98.1% and the testing accuracy is 92.73%.





Here is the confusion matrix of training and testing results respectively.



Future Work

The identification and classification of diabetic retinopathy using CNNs and architectures like MobileNet offer promising results. However, there are several areas of future work that can be explored to further improve the performance and applicability of the models. Here are some potential avenues for future research:

1. **Fine-tuning and Transfer Learning:** In the current project, the CNN models were initialized with pre-trained weights. Further exploration can involve fine-tuning the models on a larger diabetic retinopathy dataset specific to the target population. Fine-tuning allows the models to adapt to the specific characteristics of the dataset, potentially improving their classification performance. Additionally, transfer learning can be extended by leveraging pre-trained models trained on larger and more diverse medical imaging datasets, which may capture more generic features relevant to diabetic retinopathy. With some finetuning the accuracy can be increased.
2. **Ensemble Methods:** Ensemble methods can be employed to combine the predictions of multiple CNN models, such as EfficientNet and Inception. Ensemble learning has shown to enhance classification accuracy by reducing model bias and variance. Combining the strengths of different architectures can potentially lead to improved overall performance and robustness. Techniques like majority voting or weighted averaging can be used to aggregate the predictions of individual models in the ensemble.
3. **Multi-modal Integration:** The integration of multiple imaging modalities, such as retinal fundus images and optical coherence tomography (OCT) scans, can provide complementary information for diabetic retinopathy classification. OCT scans provide high-resolution cross-sectional images of the retina, enabling the detection

of additional structural abnormalities. Future work can focus on developing fusion models that combine the information from multiple modalities to improve the accuracy and reliability of diabetic retinopathy diagnosis.

4. **Exploring Advanced CNN Architectures:** Apart from EfficientNet and Inception, there are numerous other advanced CNN architectures available that can be explored for diabetic retinopathy classification. Models like DenseNet, ResNet, or NASNet have demonstrated excellent performance in image classification tasks.

5. **Interpretability and Explainability:** CNN models are often considered black boxes due to their complex nature. Enhancing the interpretability and explainability of the models can provide valuable insights into the decision-making process and build trust in their predictions. Techniques such as gradient-based visualization, saliency maps, or class activation maps can be employed to highlight the regions of interest and features that contribute most to the model's decision, aiding clinicians in understanding and trusting the model's output.

6. **Real-time Deployment and Mobile Applications:** The development of efficient models suitable for real-time deployment on mobile and embedded devices is crucial for wider adoption of diabetic retinopathy classification in clinical practice. Optimizing the models for reduced memory footprint and faster inference times can facilitate their integration into mobile applications or portable retinal screening devices, enabling early detection and remote monitoring of diabetic retinopathy.

By addressing these areas of future work, the identification and classification of diabetic retinopathy using CNNs, EfficientNet, and Inception can continue to advance, ultimately leading to improved diagnostic accuracy, better patient outcomes, and enhanced accessibility to healthcare services for individuals with diabetes.

Conclusion

The project provided a comprehensive introduction to diabetic retinopathy, its types, and the motivation behind using CNNs and specific architectures for its identification and classification. The literature review emphasized the success of CNNs in diabetic retinopathy analysis, as well as the specific architectures MobileNet, EfficientNet, and Inception. Through extensive research and experimentation, the effectiveness of these deep learning techniques in accurately detecting and classifying diabetic retinopathy has been demonstrated.

The project highlights the potential of CNNs and architectures like MobileNet, EfficientNet, and Inception for accurate identification and classification of diabetic retinopathy. These techniques offer a promising approach to aid clinicians in early detection and effective management of the disease, ultimately improving patient care in the field of ophthalmology.

The project "Identification and Classification of diabetic retinopathy" has several potential use cases and applications in the field of ophthalmology and healthcare, including:

- **Screening programs**: The model can be integrated into screening programs for DR, allowing for the efficient and automated grading of images and reducing the burden on ophthalmologists.
- **Telemedicine:** The web application developed in the project can be used for telemedicine consultations, enabling remote diagnosis and management of DR, particularly in underserved areas.

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