**Declaration of Originality**

I declare that this project is all my own work and has not been copied in part or in whole from any other source except where duly acknowledged. As such, all use of previously published work (from books, journals, magazines, internet etc.) has been acknowledged by citation within the main report to an item in the References or Bibliography lists. I also agree that an electronic copy of this project may be stored and used for the purposes of plagiarism prevention and detection.

**Statement of copyright**

I acknowledge that the copyright of this project report, and any product developed as part of the project, belong to Coventry University. Support, including funding, is available to commercialise products and services developed by staff and students. Any revenue that is generated is split with the inventor/s of the product or service. For further information please see [www.coventry.ac.uk/ipr](http://www.coventry.ac.uk/ipr) or contact [ipr@coventry.ac.uk](mailto:ipr@coventry.ac.uk).

**Statement of ethical engagement**

I declare that a proposal for this project has been submitted to the Coventry University ethics monitoring website (<https://ethics.coventry.ac.uk/>) and that the application number is listed below (Note: Projects without an ethical application number will be rejected for marking)

{AleenaAlby} Date:

Please complete all fields.

| First Name: Aleena |
| --- |
| Last Name: Alby |
| Student ID number |
| Ethics Application Number |
| 1st Supervisor Name Prof James Brusey |
| 2nd Supervisor Name |

# Introduction

One of the major causes of eye vision loss is diabetes. While delayed examination would have a higher effect on the retinal area of the eye, early detection of diabetes is crucial. The key factors affecting the rise in the occurrence of this disease are people’s lifestyles and other contributing factors, and it is anticipated that this trend will continue. According to Tien Y Wong et al, among the 285 million diabetics worldwide, 33 percent of those individuals exhibit DR symptoms([R, Ty, and C 2015](#ref-r2015)). Nearly 90% of individuals can be diagnosed, and long-term effects can be reduced, with thorough screening and regular checkups. The significant issue here is that DR is primarily an asymptomatic eye condition that does not manifest distinctive symptoms until a late stage is reached. The manual examination of retinal image features is a challenging and taxing task, nevertheless. Many automated diagnostic technologies have been created recently to help ophthalmologists examine retinal abnormalities, which has helped to solve this problem.

## Background to the Project

## Project Objectives

Can DL outperform other methods such as SVM, Logistic Regression, Decision Tree in producing a high performing classifier for DR on unseen data?

## Overview of This Report

# Literature Review

In recent years, numerous deep learning based automatic DR detection systems have emerged. In this section, some of the recent research projects have been addressed.

Using transfer learning, Esra Kaya and Ismail Saritas created CNN for the identification of diabetic retinopathy ([Kaya and Saritas 2022](#ref-9828576)). To find the best effective architecture, photographs from the DRIVE (Digital Retinal Images for Vessel Extraction) dataset of DR patients and healthy people were classified using Convolutional Neural Network (CNN) architectures as a transfer learning technique. They utilised contrast-limited adaptive histogram equalisation to improve the clarity of the image. They assessed the ResNet18, GoogleNet, and SqueezeNet CNN architectures’ performances as feature extraction techniques and classifiers. For ResNet18 and squuezeNet, they employed adam optimizer, while for googleNet, they used sgdm. There are 71 layers in ResNet18, 144 layers in GoogleNet, and 68 layers in SqueezeNet. ResNet18 was discovered to be the most effective architecture as a classifier with 100% accuracy.

Fundus images from the Kaggle opensource dataset were used by Nikhil Sathya Kumar and Dr. B. Ramaswamy Karthikeyan to identify DR using CNNs, Transformers, and MLPs ([Kumar and Ramaswamy Karthikeyan 2021](#ref-9651024)). The dataset includes more than 3600 photographs with a resolution of 2416\*1736. ResNet and EfficientNet based on CNN, Vision-Transformer and SwinTransformer based on Transformer, and MLP-Mixer based on MLP architecture were the models chosen for this study.The findings show that, in comparison to CNN and MLP based models, Transformer based models were more accurate. All models underwent 15 epochs of training. The most accurate Transformer-based model was Swin with 92.49% accuracy.

ImageNet model was proposed by Jayakumari.C et.al ([Jayakumari, Lavanya, and Sumesh 2020](#ref-9215270)). Here the TensorFlow framework is used to build a convolutional neural network model in Python. The size of each image has been reduced to 224 X 224 X 3. The model trained the network using the Adam optimizer and categorical cross-entropy as a loss function. The model was executed 100 epochs. The model accuracy in training was 98.8%, and in validation accuracy was 98.5%.

A CNN method was suggested by Frans Coenen et.al to diagnose DR with a sensitivity of 95 % and accuracy of 75% ([Pratt et al. 2016](#ref-pratt2016convolutional)).They train the network using a high-end graphics processor unit (GPU) on the publicly available Kaggle dataset.

Pathak et.al classified early-stage DR using a deep learning method ([Pathak et al. 2021](#ref-9432312)). They have employed a variety of classifier-based techniques, including SVM (Support Vector Machine), CNN (Convolution Neural Network), DCNN (Deep Convolution Neural Network), ANN (Artificial Neural Network), NB (Naive Bayes), and threshold-based strategies. The model achieved 90% accuracy for the SVM, 91% for the ANN, 92.9% for the NB, 97% for the Thresholding-Based, and 96.5% for the DCNN. They concluded that the DCNN technique is highly accurate and productive.

DR detection methods

| Methods & Ref | Datasets Used | Techniques | Performance metrics |
| --- | --- | --- | --- |
| **CNN** ([Kaya and Saritas 2022](#ref-9828576)) | DRIVE dataset (40 images in the database were chosen randomly from 400 images) | They assessed the ResNet18, GoogleNet, and SqueezeNet | ResNet18 - 100 %, GoogleNet - 68.2 %, SqueezeNet - 67.4 % |
| **CNN**, **MLP & Transfomer** ([Kumar and Ramaswamy Karthikeyan 2021](#ref-9651024)) | Aptos dataset from Kaggle (6590 Images) | EfficientNet, ResNet, MLP-Mixer, ViT , ViT+MLP, Swin and Swin+ViT | EfficientNet -91.18 %, ResNet - 89.63%, MLP-Mixer - 94.47%, ViT - 91.13 %, ViT+MLP - 89.73%, Swin - 92.49%, Swin+ViT - 91.91 % |
| **ImageNet** ([Jayakumari, Lavanya, and Sumesh 2020](#ref-9215270)) | Kaggle Dataset | ImageNet | 98.6% |
| **CNN** ([Pratt et al. 2016](#ref-pratt2016convolutional)) | Kaggle Dataset  (80,000 Images) | CNN | 75% |
| **SVM classifier-Based technique, CNN classifier, DCNN classifier, ANN classifier, NB classifier, Thresholding Based techniques**.([Pathak et al. 2021](#ref-9432312)) | Indian Diabetic Retinopathy Image Dataset (IDRiD), High-Resolution Fundus (HRF) Image Database, Kaggle dataset | Using a classifier-based SVM (Support Vector Machine) method, Convolution neural network classifiers,  DCNN (deep convolution neural network) classifiers, artificial neural network classifiers, naive bayes classifiers, and threshold-based methods are examples of classifiers. | SVM - 90%  CNN - Best  ANN - 91%  NB - 92.6%  Thresholding Based -97%  DCNN - 96.5% |

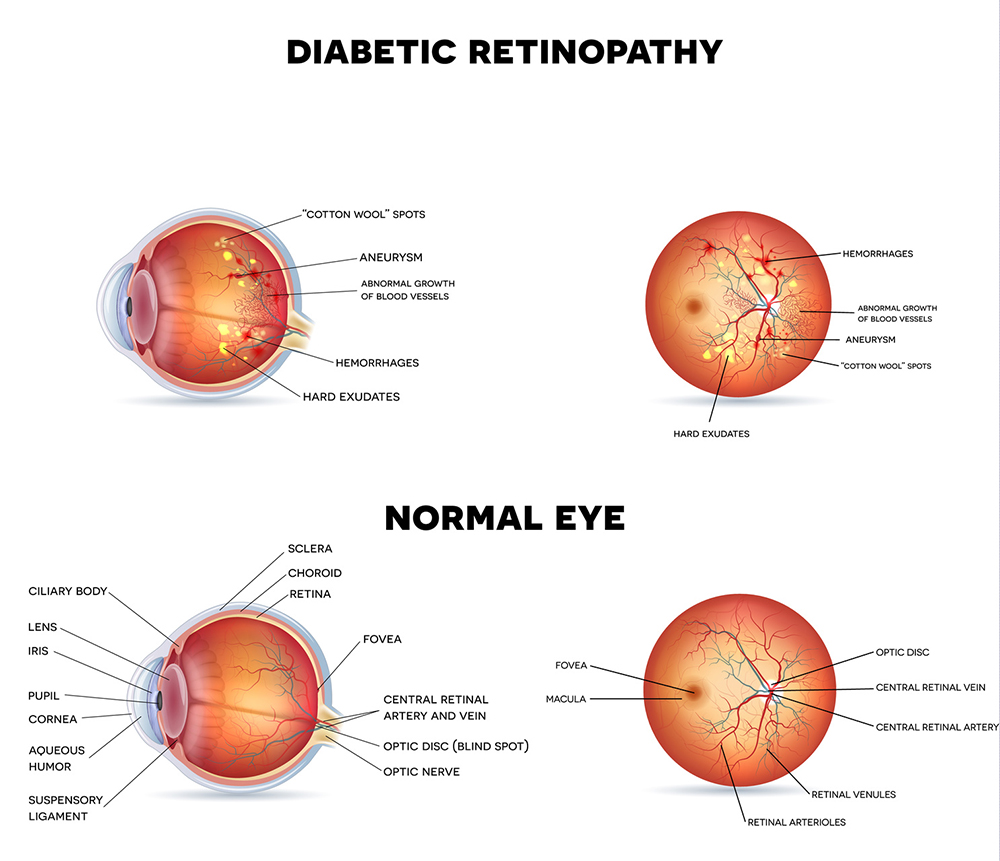
# Methodology

## *Dataset*

This study using dataset available at Kaggle([“Diabetic Retinopathy Detection” 2015](#ref-diabetica_data)). This Retinal images were provided by EyePACS. The dataset containing large set of high-resolution retina images taken under a variety of imaging conditions. For each image, a left and right field is provided. Images are identified by a image id and either the left or right eye (for example, 1 left.jpeg represents the patient number 1’s left eye).

([“Diabetic Retinopathy - Stages” 2017](#ref-diabetic2017))

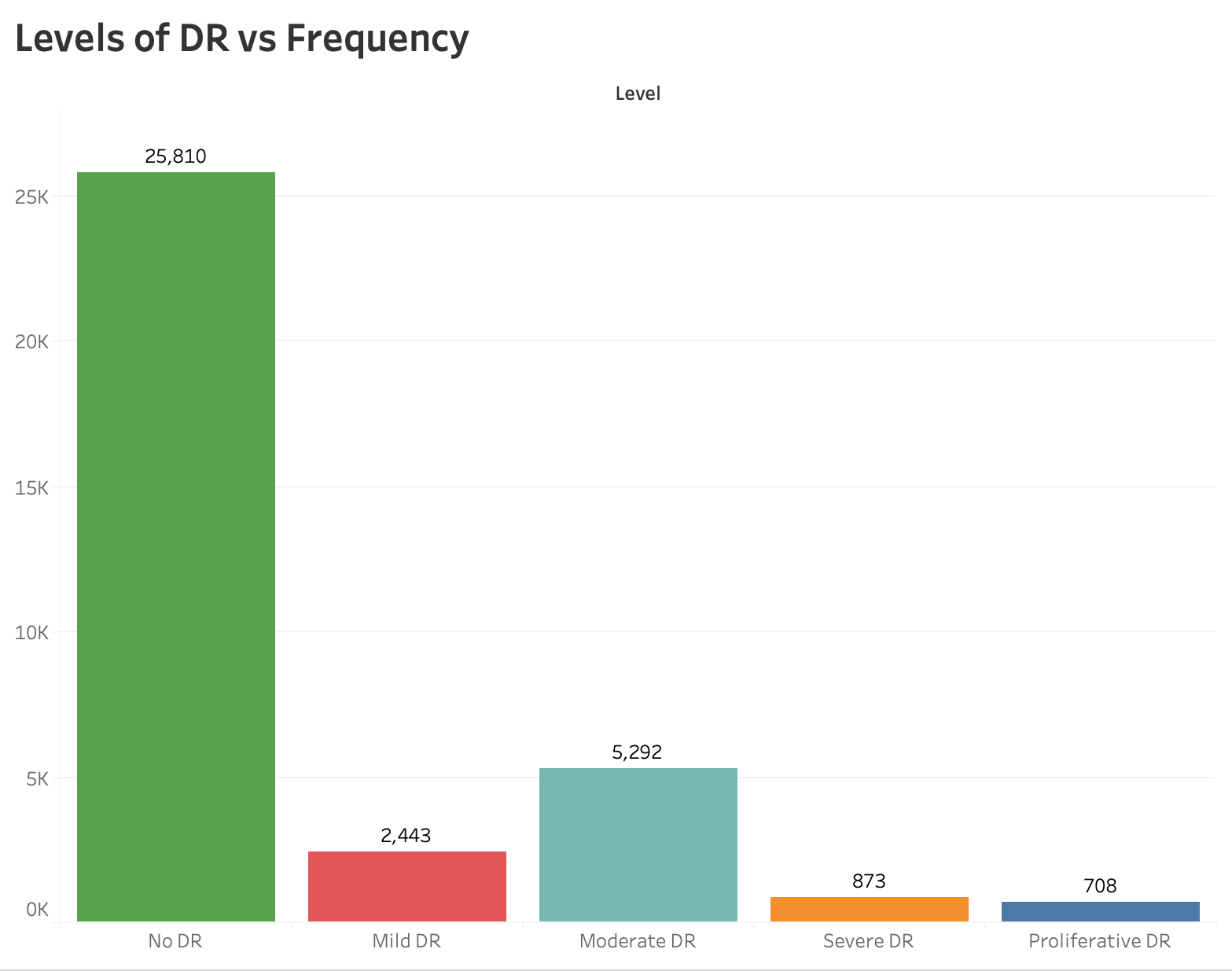
| DR classes | Level | Description |
| --- | --- | --- |
| No DR | 0 | Healthy Retina (Normal) |
| Mild | 1 | Retina with tiny bulges (microaneurysms) |
| Moderate | 2 | Retina with microaneurysms, higher risk of developing vision problems in the future |
| Severe | 3 | Retina with severe and widespread microaneurysms, including bleeding into the retina |
| Proliferative | 4 | New blood vessels and scar tissue have formed on your retina, which can cause significant bleeding and lead to retinal detachment |



Normal Retina Vs Diabetic Retinopathy Retina ([“Diabetic Retinopathy Vs Normal,” n.d.](#ref-diabetica))

## *Data pre-processing*

Image pre-processing was performed with the aim to decrease unclear image and reduce image size. The plot below illustrates the class imbalance in the original dataset.



Sum of number of records for each level

The dataset consist of 35,126 set of images. The orginal image have 1944 \* 2592 \* 3 size, and all images are jpeg format. The classes have an uneven distribution of images.

1. Image Resizing

* Due to the enormous size of the dataset, it was drastically downsized before being sent to the network. Each input image is 256 \* 256 in size after resizing.

1. Removing Unclear Image

* Some images have a blackish or white tint. Because it might affect the outcome, this type of image cannot be fed into the network. The removal of an unclear image is a crucial step that must be taken.

1. Dividing images into classes

* Images are classified into 5 folders based on the DR levels.

# Requirements

# Analysis

# Design

# Implementation

# Testing

# Project Management

## Project Schedule

## Risk Management

## Quality Management

## Social, Legal, Ethical and Professional Considerations

# Critical Appraisal

# Conclusions

## Achievements

## Future Work

# Student Reflections

# References

“Diabetic Retinopathy - Stages.” 2017. <https://www.nhs.uk/conditions/diabetic-retinopathy/stages/>.

“Diabetic Retinopathy Detection.” 2015. <https://kaggle.com/competitions/diabetic-retinopathy-detection>.

“Diabetic Retinopathy Vs Normal.” n.d. <https://www.advancedretinaassociates.com/patient-education/diabetic-retinopathy/>.

Jayakumari, C., Vidhya Lavanya, and E P Sumesh. 2020. “Automated Diabetic Retinopathy Detection and Classification Using ImageNet Convolution Neural Network Using Fundus Images.” In *2020 International Conference on Smart Electronics and Communication (ICOSEC)*, 577–82. <https://doi.org/10.1109/ICOSEC49089.2020.9215270>.

Kaya, Esra, and Ismail Saritas. 2022. “Performances of CNN Architectures on Diabetic Retinopathy Detection Using Transfer Learning.” In *2022 57th International Scientific Conference on Information, Communication and Energy Systems and Technologies (ICEST)*, 1–4. <https://doi.org/10.1109/ICEST55168.2022.9828576>.

Kumar, Nikhil Sathya, and B. Ramaswamy Karthikeyan. 2021. “Diabetic Retinopathy Detection Using CNN, Transformer and MLP Based Architectures.” In *2021 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, 1–2. <https://doi.org/10.1109/ISPACS51563.2021.9651024>.

Pathak, Ketki C., Riddhi B. Shah, Reshma R. Tharakan, Bhavya N. Patel, and Dhruvi C. Jariwala. 2021. “Diabetic Retinopathy Diagnosis and Categorization Using Deep Learning - a Review.” In *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 1063–69. <https://doi.org/10.1109/ICICCS51141.2021.9432312>.

Pratt, Harry, Frans Coenen, Deborah M Broadbent, Simon P Harding, and Yalin Zheng. 2016. “Convolutional Neural Networks for Diabetic Retinopathy.” *Procedia Computer Science* 90: 200–205.

R, Lee, Wong Ty, and Sabanayagam C. 2015. “Epidemiology of Diabetic Retinopathy, Diabetic Macular Edema and Related Vision Loss.” *Eye and Vision (London, England)* 2 (September). <https://doi.org/10.1186/s40662-015-0026-2>.

Appendix A – Project Specification

Appendix B – Interim Progress Report and Meeting Records

Appendix C – Requirements Specification Document

Appendix D – User Manual

Appendix E – Project Presentation

Appendix F – Certificate of Ethics Approval