# A ROBUST TRANSFER LEARNING BASED MODEL TO PREDICT DIABETIC RETINOPATHY

**BY**

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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## APPROVAL

This Project titled **"A ROBUST TRANSFER LEARNING BASED MODEL TO PREDICT DIABETIC RETINOPATHY"**, submitted by Sanzida Akter Mukti, ID No: 191-15-2346 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 05-02-2023.

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# DECLARATION

I hereby declare that, this project has been done by us under the supervision of **Dr. S. M. Aminul Haque, Associate Professor, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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# ABSTRACT

Millions of people throughout the world are affected by the disease known as diabetic retinopathy each year. As DR disorders can have a significant impact on patients' eyes and quality of life, early disease diagnosis is a crucial area of medical research. Deep Learning approaches have developed quickly for computer vision applications as a result of an abundance of data accessible for model training and improved model designs. In this paper, a strong deep-learning CNN model that performs ablation studies to classify DR illness will be described. By removing artifacts, lowering noise, and enhancing the image, the disease is colored and the overall quality is improved. The quantity of DR disease photographs has expanded because to enhancement techniques. The supplemented dataset initially proposes a base CNN model. Our suggested model, the robust CNN model, was obtained through an ablation study. A collection of freely accessible photos of DR diseases are used to train the model. With accuracy of 93.28%, the suggested robust model produced the best results. The model is solid and has excellent generalizability on new data. In cases involving the detection of binary and multi-class diabetic retinopathy diseases, the model also obtains a high level of precision and recall.

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# CHAPTER 1

# Introduction

## 1.1 Introduction

One of the main reasons for the increase in blindness worldwide is diabetic retinopathy (DR). There are 415 million diabetes individuals globally, according to data. Diabetic patients need to be tested annually to prevent blindness. A number of factors make early detection of DR difficult, though. First, many patients' treatment for diabetes is delayed because fundus examinations have long been disregarded in endocrinology departments, where diabetics often receive care. Second, because DR screening requires a lot of time, a set number of patients can be processed each day. Third, there aren't enough ophthalmologists to keep up with the demand, especially in developing countries [1]. Nearly 45% of patients in India are blind before receiving a diagnosis, despite the country having almost 127,000 ophthalmologists. This shouldn't occur as diabetic retinopathy is entirely avoidable. The Google research team closely collaborated with EyePACS in the USA and three eye hospitals in India to make improvements to this scenario [2]. Numerous groups have researched the automated analysis of retinal color pictures for DR over the past 20 years. Comparison is challenging because there aren't many well-known, comprehensive, and representative datasets, yet recent studies suggest that full DR screening systems using such algorithms offer appropriate safety, for example the Iowa Detection Program, notwithstanding the difficulty in comparison due to the lack of widely acknowledged, well defined, and representative datasets (IDP[3]. In 12 of 35 investigations, the prevalence of the condition was determined to be 34.6% overall for diabetic retinopathy in general, 10.2% for diabetic retinopathy that poses a threat to vision, and 6.8% for diabetic macular oedema. According to the limited published statistics from sub-Saharan nations, diabetic retinopathy prevalence ranges from 7% to 63%, and during the next 10 years, an increase in the percentage of blindness related to diabetic retinopathy is anticipated [4].

The purpose of this study is to develop a model which can detect DR early in the stage. This project aims to create a reliable algorithm that can classify DR across the dataset with various properties. The dataset used in this study has five classes. The files include information on five different forms of DR, such as no DR (Grade 0), mild NPDR (Grade 1), moderate NPDR (Grade 2), severe NPDR (Grade 3), and PDR (Grade 4) at an early stage by utilizing different computer vision techniques. For a CNN model to operate at its best, artifacts must be eliminated. Through an ablation investigation, the deep learning model for DR diagnosis proposed in this paper is fully automated and trustworthy. An ablation study is conducted on the model with the best accuracy using five study examples in order to increase the model's overall accuracy and resilience. After creating the proposed model, it was trained using the dataset. This demonstrated that our hypothesis was accurate because the model performs at its best for the datasets. Additionally, the proposed model’s performance consistency is evaluated by contrasting it with the output of three current pre-trained and optimized transfer learning (TL) architectures, namely VGG16, VGG19, MobileNet, MobileNetV2 and InceptionV3, across dataset. The False Positive Rate (FPR), False Negative Rate (FNR), False Discovery Rate (FDR), Mean Absolute Error (MAE), and Root Mean Squared Error are performance indicators used to assess each experiment's performance (RMSE). The tested MobileNetV2 model had a test accuracy of 87.22% and after ablation study the accuracy reached 93.28%. The repeatable results of this study demonstrate that the transfer learning approach, in combination with ablation studies and image processing techniques, can speed up diagnosis, potentially assisting clinical experts significantly in the treatment of DR.

## 1.2 Motivation

Manually identifying DR from retinal pictures presents a challenge because it takes a lot of time, and there aren't many specialists. In order to address this issue, it would be beneficial to develop an automated method for detecting diabetic retinopathy that could function without the aid of a medical professional. Given a large dataset of labeled examples and a class of machine learning techniques known as deep learning, computers may discover the most predictive features from images without explicitly setting any rules or attributes [5]. An ophthalmologist and an ophthalmic medical photographer work together to grade diabetic retinopathy images from the Otago Diabetic Eye Monitoring Service (ODEMS) in Dunedin Hospital [6]. In order to identify diabetic retinopathy, some researchers have used deep convolutional neural networks (CNN).

## 1.3 Rationale of the Study

a) To create a reliable algorithm that can classify DR across the dataset with various properties.

b) To use data augmentation to solve the data imbalance problem.

c) To preprocess the image by denoising, image enhancing and artifacts remove.

d) To find out the best transfer learning model for DR prediction.

e) To make the transfer learning model more robust by performing ablation study.

## 1.4 Research Questions

a) How can we improve DR prediction system by finding the research gaps in existing machine vision-based systems for correctly classifying different DR types?

b) Which augmentation and preprocess will match perfectly to predict Diabetic Retinopathy?

c) How can we develop a robust model for improving the accuracy for classify DR according to their class?

## 1.5 Project Management and Finance

This research based project didn’t receive any financial support from any group or company.

## 1.6 Report Layout

Chapter 1 presents the research introduction, objectives, and key research questions.

Chapter 2 brief summaries of the literature review are provided.

Chapter 3 describes the proposed methodology with a detailed description.

Chapter 4 explains paper's experimental results and discussed.

Chapter 5 concludes the present research along with a direction for future work.

# CHAPTER 2

# Background

## 2.1 Related works

To categorize eyes, researchers have suggested a variety of deep-learning and machine learning techniques. We give some research from the literature in this area that used datasets for common eye illnesses to categorize diseases.

Sehrish et al. [7] introduced a group of 5 deep Convolutional Neural Network (CNN) models. They are Resnet50, Xception, Inceptionv3, Dense169, and Dense121 to encode the rich characteristics and enhance the classification for various phases of DR using the publicly available Kaggle dataset of retinal pictures. On the same Kaggle dataset, the experimental findings demonstrate that the model which was proposed, outperforms other transfer learning methods and detects all stages of DR, in contrast to the present methods.

Akhilesh et al. [2] proposed Inception-ResNet-v2 is pre-trained using transfer learning, and a custom block of CNN layers is built on top of Inception-ResNet-v2 to create the hybrid model. They assessed the suggested model's performance using the Messidor-1 dataset for diabetic retinopathy and the APTOS 2019 blindness detection (Kaggle dataset). Comparing their model's performance to previous published findings. On the Messidor-2 and APTOS datasets, they respectively attained test accuracy of 72.33% and 82.18%.

Convolutional neural network algorithms, which combine deep learning as a major element and are speeded up with GPUs (Graphics Processing Units), are used by Lifeng et al. [8] to analyze whether a microaneurysm is present in a fundus image. This system will perform medical image detection as well as segmentation with fast and low-latency inference. The semantic segmentation method is utilized to assess if the fundus picture is clean or contaminated. It has been proposed to use the Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy, which is capable of efficiently training a deep CNN for segmentation of fundus images, which can increase the effectiveness and precision of NPDR (non-proliferated diabetic retinopathy) prediction.

Zhentao et al. [9] have created a dataset of DR fundus pictures that has been annotated with the necessary treatment approaches. They built deep convolutional neural network models on this dataset to categorize the severity of DR fundus pictures. In the experiments, they were able to reach an accuracy of 88.72% for a four-degree classification challenge. In the clinical evaluation, the system achieved a consistency rate of 91.8% with ophthalmologists, confirming the efficacy of their work. They placed their models on a cloud computing platform and provided pilot DR diagnostic services for multiple hospitals.

Borys et al. [10] putted forth a deep learning-based automatic technique for detecting the stage of diabetic retinopathy using a single image of the human fundus. The multistage strategy to transfer learning that they also suggest uses comparable datasets with various labeling. On the Messidor-2 Blindness Diagnosis Dataset, the provided approach, which has a accuracy of 90.09% and sensitivity and specificity of 0.99 and is ranked 54 out of 2943 competing methods (quadratic weighted kappa score of 0.925466), can be utilized as a screening method for the early detection of diabetic retinopathy (13000 images).

Emma et al. [11] showed that a number of socio-environmental factors have an effect on model performance, nurse workflows, and patient experience. They use these findings as a springboard for discussion about the merits of doing human-centered evaluation research in tandem with future assessments of model correctness.

Mamta et al. [12] presented the problem by utilizing a deep learning algorithm that automatically recognizes the pattern and categorizes the retinal images into one of the five class based. They achieved the highest validation accuracy of 74.4% on Messidor-2 datastet.

Shankar et al. [13] detected and categorized DR from Messidor-2 color fundus images, a novel automated Hyperparameter Tuning Inception-v4 (HPTI-v4) model is introduced in this study. The contrast level of the fundus picture will be raised during the preprocessing step by employing the contrast limited adaptive histogram equalization (CLAHE) model. The preprocessed image is then segmented using a segmentation model based on histograms. They provided the HPTI-v4 model, which has the highest accuracy, sensitivity, and specificity of 95.49%, 94.83%, and 96.68%, respectively, clearly producing exceptional results. For the classification of DR images, the given model can be used as an automated diagnostic tool.

Filippo et al. [14] demonstrated the viability of using patient CFPs collected at a single visit to forecast the evolution of DR in the future. Such an algorithm could facilitate early identification and referral to a retina specialist for more frequent monitoring and treatment if it were to be further developed on larger and more diversified datasets, even taking early intervention into account. Additionally, it might enhance the patient pool for clinical studies focusing on DR. With an area under the curve (AUC) of 0.68 0.13 (sensitivity, 66% 23%; specificity, 77% 12%), 0.79 0.05 (sensitivity, 91% 8%; specificity, 65% 12%), and 0.77 0.04 (sensitivity, 79% 12%; specificity, 72% 14%), respectively.

In multicultural communities with diabetes which are found in community and clinic settings, Daniel et al. [15] examined how well a DLS performed in predicting referable diabetic retinopathy, vision-threatening DR, probable glaucoma, and age-related macular degeneration (AMD). In the primary Messidor-2, the percentage of referable DR was 3.0%, vision-threatening DR were 0.6%, AMD was 2.5% and probable glaucoma was 0.1%. The AUC score of the DLS for referable diabetic retinopathy was 0.936, the accuracy was 91.6% and the sensitivity was 90.5%.

Yashal et al. [16] focuses on the idea of employing a deep learning model to categorize photos of DR fundus according to the severity level. The automated identification and classification algorithm for fundus images of diabetic retinopathy (DR) is proposed in this research and is based on deep learning. Preprocessing, segmentation, and classification are some of the procedures that the suggested method entails. To begin with, the preprocessing stage is completed to remove the extra noise present in the edges. To extract the useful sections from the image, histogram-based segmentation is then performed. The next step is to classify DR fundus photos according to various severity levels using a synergic deep learning (SDL) model. On the Messidor-2 DR dataset, the justification of the given SDL model is done. Additionally, it should be highlighted that the AlexNet model achieves the least classification, with a classifier accuracy of 89.75 as the lowest. With the greatest accuracy of 99.28, sensitivity of 98.54, and specificity of 99.38, the provided SDL model clearly exhibits outstanding classification, as shown by the table data.

## 2.2 Scope of the Problem

We can see from the previous studies that, several machine and deep learning based already employed to classify diabetic retinopathy (DR). However, there are drawbacks such as lower accuracy, time efficiency, lack of using data augmentation, and pre-processing methods. Our study have tried to address these issues and developed a robust model to classify DR.

## 2.3 Challenges

The focused challenges for this research are:

1. **Dataset**: To train and test this model, different datasets with various classes must be gathered.
2. **Data Augmentation:** To increase the size of the datasets, data augmentation techniques must be used. Using a variety of image pre-processing methods, challenging artifacts are eliminated and the image quality is improved.
3. **Image Processing:** Images from various sources were sometimes noisy or low-contrast. Creating noise-free, contrast-enhanced classification images is difficult.
4. **Select Base Model:** A perfect base model for ablation studies is needed to address long training times and insufficient data.
5. **Propose a Robust Model and Improve Accuracy:** To classify DR more accurately, we use a CNN-attention hybrid model.

# CHAPTER 3

# Research Methodology

## 3.1 Working Process

The whole working process is showed in figure 3.1 below.

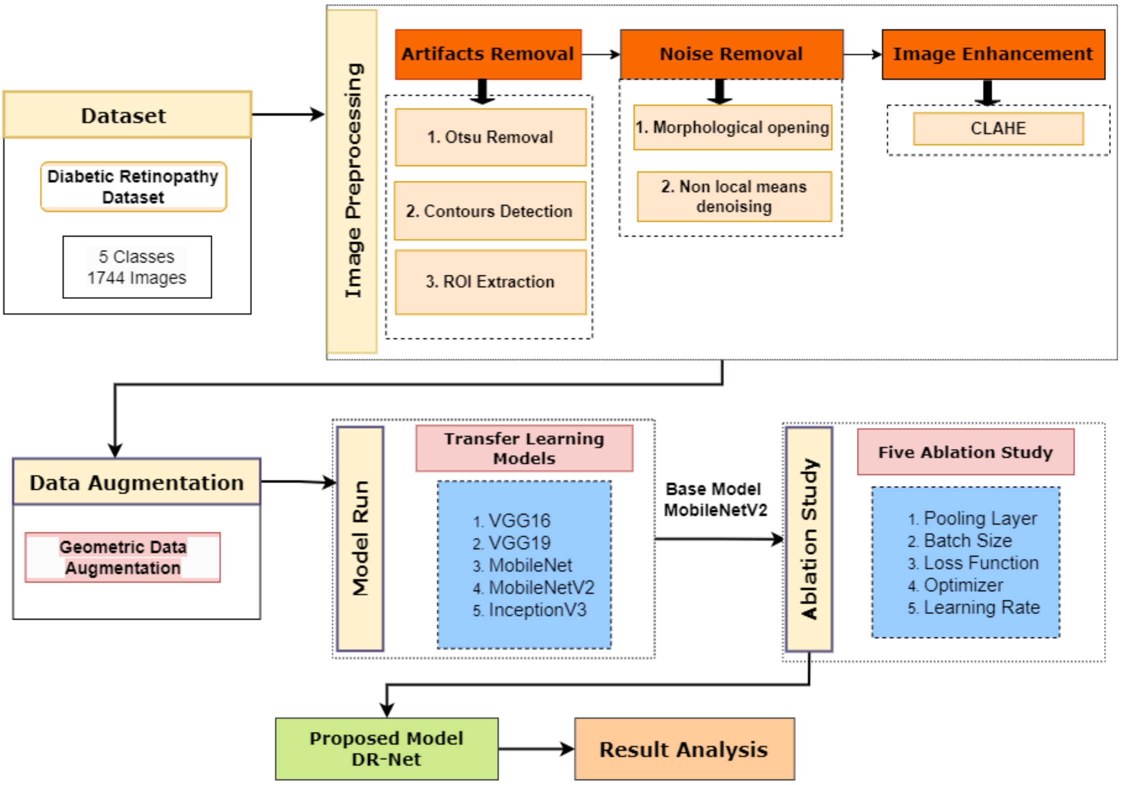



**Fig 3.1:** Whole methodology to perform loan prediction

To evaluate the entire approach, a publicly available diabetic retinopathy dataset consisting of 5 classes and 1744 photos is collected from Kaggle. Several picture preprocessing techniques, such as artifact removal, noise removal, and image enhancement, are then implemented to improve the image quality. We used otsu removal, contours detection, and ROI extraction to eliminate the artifacts. Morphological opening and non-local means denoising have been conducted to reduce image noise, and CLAHE has been performed to improve image quality. After picture preprocessing, a data augmentation technique known as geometric data augmentation is carried out. The augmented images were then sent to transfer learning models named VGG16, VGG19, MobileNet, MobileNetV2, and Inception V3. After processing the images across transfer learning models, the model with the best performance is selected as the basic model for the ablation research. Five ablation studies, including pooling layer, batch size, loss function, Optimizer, and learning rate, are undertaken to create a more robust base model for diabetic retinopathy multiclass classification. The DR-Net robust model is proposed. Multiple result analyses have been conducted to demonstrate the performance of the suggested model. The subsequent sections will detail each part of the methodology.

## 3.2 Dataset Description

We utilized the Messidor2 Diabetic Retinopathy Dataset from the popular data source Kaggle [17]. The dataset has 5 classes with 1744 images. The name of the five dataset classes is: no DR (Grade 0), mild NPDR (Grade 1), moderate NPDR (Grade 2), severe NPDR (Grade 3) and PDR (Grade 4). NDPR is Non- Proliferative Diabetic Retinopathy.

Each dataset contains various number of images like, No DR (Grade 0) contains 1017 images, Mild NPDR (Grade 1) contains 270 images, Moderate NPDR (Grade 2) contains 347 images, Severe NPDR (Grade 3) contains 75 images and PDR (Grade 4) contains 35 images.

However, the distribution of the sample is not equal, and there are artifacts in the images. In this work, we performed multiple image preprocessing operations to increase the quality of the image.

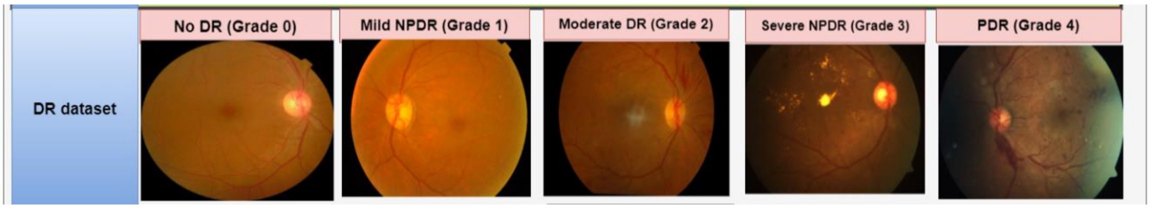



**Fig 3.2:** Images from the different classes of DR Dataset.

## 3.3 Image Pre-processing

The practice of applying different methods to an image in order to enhance it or extract useful information from it is known as image pre-processing. It is a form of signal processing in which an image serves as the input, and the output can either be an additional image or attributes or properties associated with the original image. As a result, images are improved for human interpretation. Data can be taken from images and used for automated interpretation. The pixels in the image can be changed to produce any desired density and contrast. It is possible to easily access and store images.

Several image preprocessing techniques are applied to remove the artifacts, noise remove and enhance the image. The details are discussed below:

### 3.3.1 Artifacts Removal

Any feature that appears in a picture but is absent from the original object that was imaged is known as an image artifact. Sometimes a picture artifact is the result of the imager operating improperly, and other times it is a result of physiological processes or characteristics of the human. To remove artifacts, we used otsu removal, contours detection and ROI extraction.

a) **Otsu Removal:** Image thresholding is a technique used by the Otsu method to segregate similar data. The appropriate global threshold value is determined by the Otsu method using an image histogram. Here, retinal fundus images are thresholder using the Otsu method to separate the background from the ROI. A grayscale image is converted into a binary image using this nonlinear process. The algorithm typically takes a grayscale image as input, and produces a binary image whose intensity depends on the pixel intensity of the input image. The associated output pixel is recorded as white if the intensity of a pixel exceeds the threshold. In contrast, the output pixel is recorded as 0 or black if the intensity of an input pixel is equal to or lower than the threshold**.**

b) **Contours Detection:** Contour detection uses a method to extract curves that match the shapes of objects in photos. A contour is an outline that indicates or confines the shape or form of an object. The binary image from Otsu's thresholding is used as a source image in the cv2.findContours() method, which can identify the contours of the retinal fundus image. The contours are located, and then using a sort function, they are arranged from greatest to smallest in terms of area. The contour list and a key with the value cv2.contourArea are the two arguments supplied to the function.

c) **Extraction of Regions of Interest (ROI)**: A sampling within a data set that has been identified for a specific purpose is called a region of interest (commonly shortened as ROI). The term "ROI" is frequently used in a variety of application fields. Our target area in the retinal fundus image for categorizing diabetic retinopathy is the region of interest area. Using the sorted contours list as input, the cv2.boundingRect() function is used to divide up this area. Numbers corresponding to x, y, w, and h are returned by the cv2.boundingRect() function, correspondingly. The width, height, Y coordinates, and X coordinates are all represented by these values. These values are used to crop the region of interest using pixel coordinates.

### 3.3.2 Noise Removal

Noise typically deteriorates fundus images, and low contrast can also cause problems. Due to these issues, it is difficult to recognize and interpret illnesses from retinal fundus pictures. [18]. We first employ morphological opening to reduce the noise in the dataset's images, and then we apply nonlocal means denoising to completely eliminate the noise.

a) **Morphological Opening:** Morphological opening [19]blackens small objects and removes any single-pixel artifacts like noisy spikes and tiny spurs. Morphological opening requires binary image conversion. Thus, binary conversion magnifies minor noises. The binary image is morphologically opened using a kernel. The artifacts to be removed shape and size this kernel. After testing several kernel shapes and sizes, a 5×5 rectangle kernel removes artifacts while preserving vital information. Thus, a noise-free binary mask is created and mixed with the original picture using bitwise AND**.** Opening erodes and dilates an image utilizing the same structuring element. Morphological opening removes small things and thin lines while keeping the size and shape of larger objects**.**

b) **Non-Local Means Denoise (NLMD):** The fundamental idea behind the NLMD algorithm [20] is to replace a pixel's color with its neighbours' average color. Compared to local mean approaches, this results in a noticeably better post-filtering clarity and less loss of image detail. The use of NLMD helps to make the photos less noisy. The following procedure is used to denoise an image with the dimensions z = (z1; z2; z3) in channel I to pixel j.[20]

$$\widehat{z_i}(x) = \frac{1}{C(x)} \sum_{k \in B(x,r)} z_i(x)\omega(x,k), \quad (1)$$

$$C(x) = \sum_{k \in B(x,r)} \omega(x,k) \quad (2)$$

here, $B\ (x,r)$ denotes the area of pixels $x$ inside a radius of $r$. The weight $\omega(x,k)$ is determined by the squared Frobenius norm distance between color patches with centers at $x$ and $k$ that degrade under a Gaussian kerne

### 3.3.3 Image Enhancement

Digital images are modified during the process of image enhancement to provide outcomes that are better suited for display or additional image analysis. To make it simpler to spot important details, we can, for instance, remove noise from an image or sharpen or brighten it. To enhance the image, we have used CLAHE.

a) **Contrast limited adaptive histogram equalization (CLAHE):** To correct excessive contrast amplification and restore general contrast balance, CLAHE is used. CLAHE is a variant of adaptive histogram equalization that addresses this noise amplification problem by restricting contrast amplification. In CLAHE, the slope of the transformation function determines the contrast enhancement near a specific pixel value.

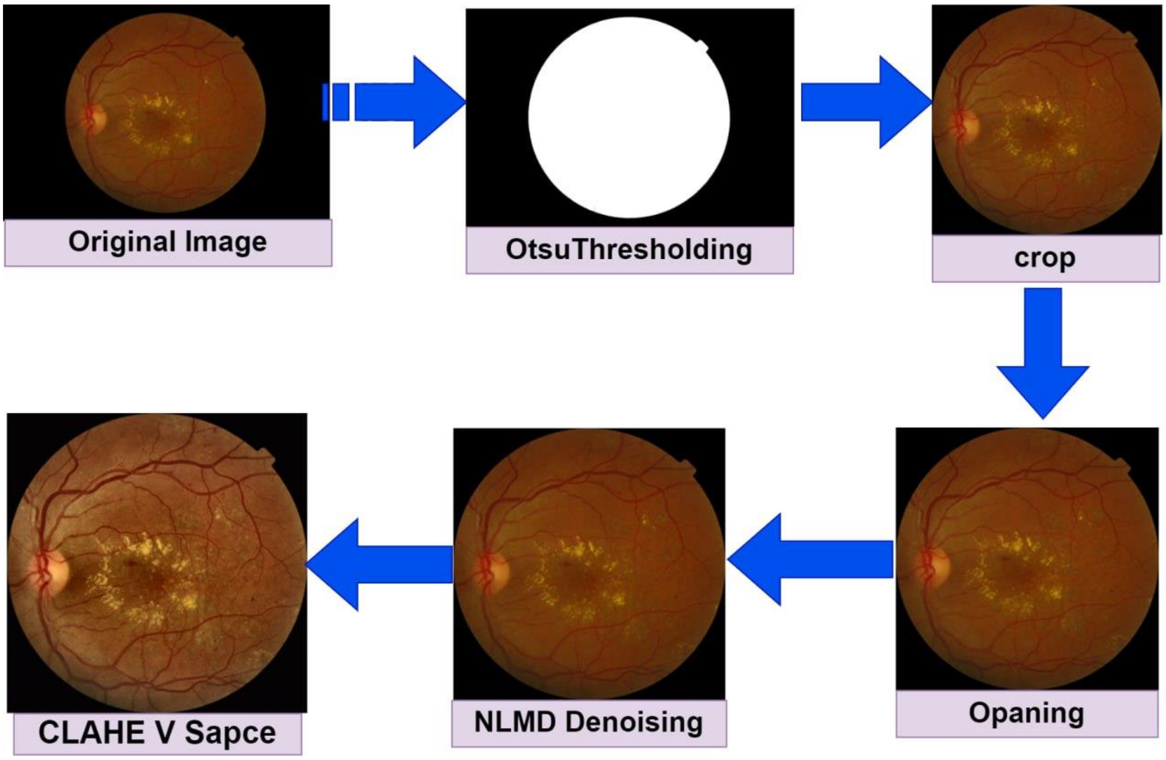



**Fig 3.3:** Followed steps for the image pre-processing

## 3.4 Data Augmentation

In our investigation, data augmentation [21] was used to balance the dataset. Overfitting problems can be avoided using a variety of methods however, data augmentation is seen as a key duty. Techniques for augmentation-based oversampling are commonly employed to boost variety and reduce potential overfitting. The amount of data should be increased effectively in order to produce samples that are representative of all potential images and balance the datasets. Another challenge is maintaining picture quality, particularly in the medical field where keeping image features may be crucial. As a result, the augmentation approach needs to produce the photographs without degrading their quality. We employ the following augmentation approaches in our study: geometric augmentation.

a) **Geometric Data Augmentation:** Geometric transformation augments data. Geometric augmentation alters an image's geometry by matching values. It improves image quality by changing its form. Medical imaging research has employed geometric augmentation approaches. Vertical flipping, horizontal flipping, vertical and horizontal flipping maintaining the image's natural horizontal-vertical column structure, and rotation by rotating the images to any degree are the most common geometric augmentation techniques we used in our study to increase dataset size.

As we already saw the dataset unbalancing problem in our dataset description section. The least number of pictures are found in severe NPDR (grade 3), PDR (grade 4), and mild NPDR (grade 1). Moderate NPDR has 4.33 times as many photos as severe NPDR, whereas No DR has 8.64 times as many images, indicating a major imbalance. In order to balance the photographs of each class, we have adopted certain measures. Table 3.1 showing the balanced dataset for each class after applying geometric data augmentation.

Table 3.1: Image counts details of original and augmented datasets

| **Dataset Classes** | **Images without augmentation** | **Images with augmentation** |
|---|---|---|
| No DR (0) | 1017 | 3051 |
| Mild NPDR (1) | 270 | 1350 |
| Moderate NPDR (2) | 347 | 1735 |
| Severe NPDR (3) | 75 | 525 |
| PDR (4) | 35 | 315 |
| Total Images | 1744 | 6976 |

## 3.5 Proposed Methodology

Before settling on the optimum transfer learning model for the classification problem, this study tested five different models in an effort to find the most effective one based on accuracy.

The Model for Learning Transfer In total, five pre-trained networks (InceptionV3, MobileNetV2, MobileNet VGG16, and VGG19) have been trained on training data and evaluated on testing data [22].

### 3.5.1 VGG16

One of the greatest image classification models, VGG 16 is very effective, simple to use, and has been applied in numerous computer vision applications. The DCNN model known as VGG16 was first introduced by Simonyan and Zisserman. In many applications, it serves as the basis model because of its excellent performance on the ImageNet dataset. Its key benefit is that it can be trained on a minimal amount of data while still performing well. Studies on the effectiveness of transfer learning have shown that a pre-trained VGG16 provided accuracy that was significantly higher than a fully trained network. The increased depth of the VGG model may enable the kernel to learn more complex properties. Fig 3.4 showing the architecture of VGG16 [23].

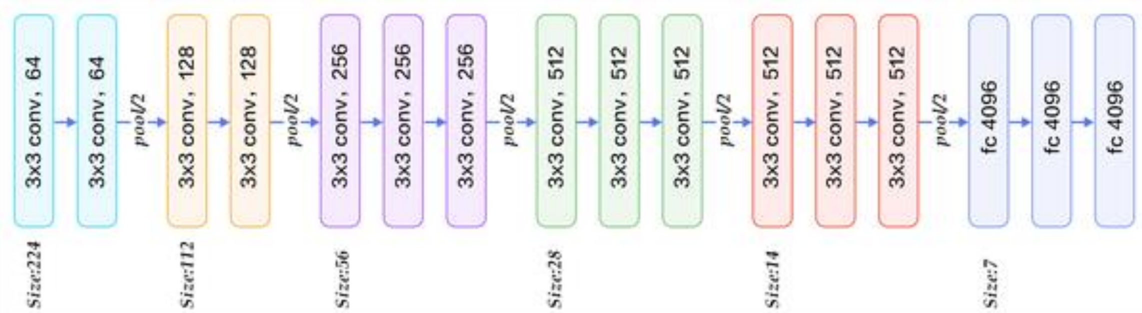



**Fig 3.4:** Architecture of VGG16

### 3.5.2 VGG19

The Visual Geometry Group (VGG) at the University of Oxford created the convolutional neural network model known as VGG19. The ImageNet dataset, which comprises of millions of tagged photos from numerous categories, served as its training data. VGG19 is a deep convolutional architecture model with 19 layers. The model was created to accurately identify and categorize photos. 13 convolutional layers and 5 fully linked layers make up the model. A batch normalizing layer and a ReLU activation layer come after each convolutional layer. The max-pooling layer in the model is also utilized to shrink the size of the feature maps. Fig 3.5 showing the architecture of VGG19 [24].

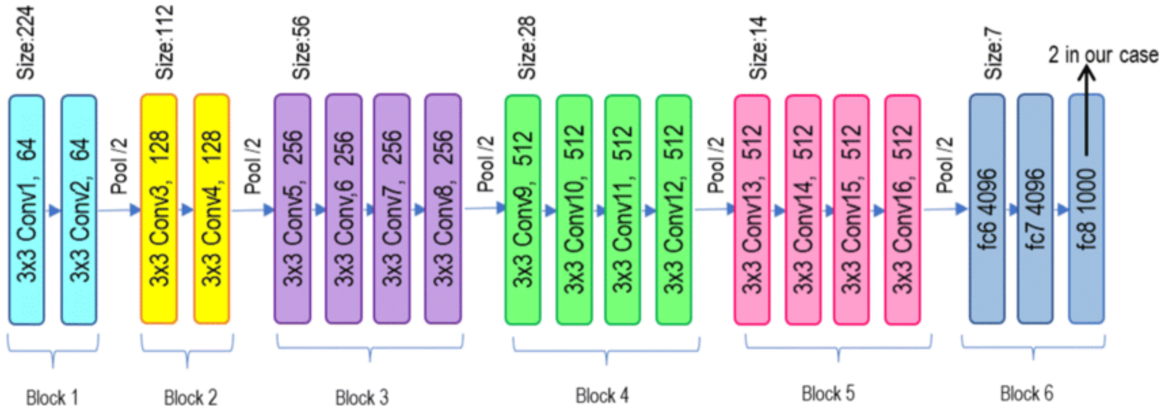



**Fig 3.5:** Architecture of VGG19

### 3.5.3 MobileNet

Google created the deep learning model MobileNet with the goal of creating a low latency, effective mobile vision solution. It is a compact convolutional neural network (CNN) made for mobile and embedded systems, including tablets, smartphones, and embedded vision software. MobileNet is made to be computationally effective and to minimize the number of network activities every frame in order to decrease latency. By substituting depth-wise separable convolution layers for numerous convolutional layers, it improves accuracy while reducing the number of parameters and processing operations. The model is built on a convolutional layer architecture with a combination of 1–1 and 3–3 layers, where 1–1 layer is used to reduce the number of parameters and 3–3 layers are used to broaden the network's receptive field. To make the feature vector less dimensional, the network also employs a global average pooling layer at the very end.

### 3.5.4 MobileNetV2

MobileNetV2 is a convolutional neural network that is lightweight and optimized for mobile use. It is an enhanced version of MobileNetV1, which was created with the goal of achieving high accuracy while minimizing model size and computational complexity. Because MobileNetV2's architecture is more effective than that of its predecessor, it can operate with greater accuracy on the same hardware. Additionally, it is made to be more resistant to hostile attacks and other forms of input noise. MobileNetV2 is made to save battery life and minimize latency on mobile devices in addition to the increased accuracy and resilience. Due to this, it is particularly well suited for usage in applications like image segmentation and object detection. MobileNetV1 can be swapped out for MobileNetV2, which is likewise compatible with current models. It consists of two different types of blocks, each with three levels. Each block includes 11 convolutional layers, the first, third, and second of which contain 32 filters. Longitudinal bottlenecks between layers are crucial to preventing non-linearity from damaging a sizable amount of data. The strides of the two blocks are different, with block 2 having a stride of two and block 1 having a stride of one. Fig 3.6 showing the architecture of MobileNetV2 [25].

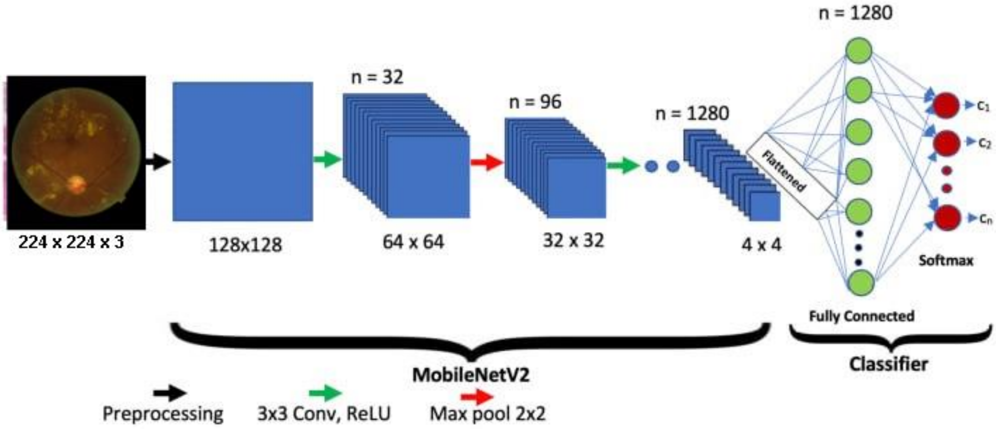



**Fig 3.6:** Architecture of MobileNetV2

### 3.5.5 Inception V3

Google created the Inception V3 convolutional neural network architecture for the 2015 ImageNet Large Visual Recognition Challenge. It is a deep learning model made to capture both local and global aspects of an image that includes components from several kinds of neural networks. It is frequently used for image classification tasks and was the winning submission for the 2015 ImageNet challenge. Each module in the Inception V3 architecture is created to extract a certain kind of information from the input image. It consists of a stack of fully connected, pooling, and convolutional layers. The local features of an image are captured by the convolutional layers, whilst the global features are captured by the pooling layers. To create a prediction, the local and global features are combined using the fully linked layers. Due to Inception V3's outstanding performance on the ImageNet challenge, it is frequently utilized for picture classification jobs. Other uses for it include image production, object identification, and image segmentation. In addition, transfer learning, in which a previously trained model serves as the foundation for training a new model, also makes use of Inception V3. Fig 3.7 showing the architecture of Inception V3 [26].

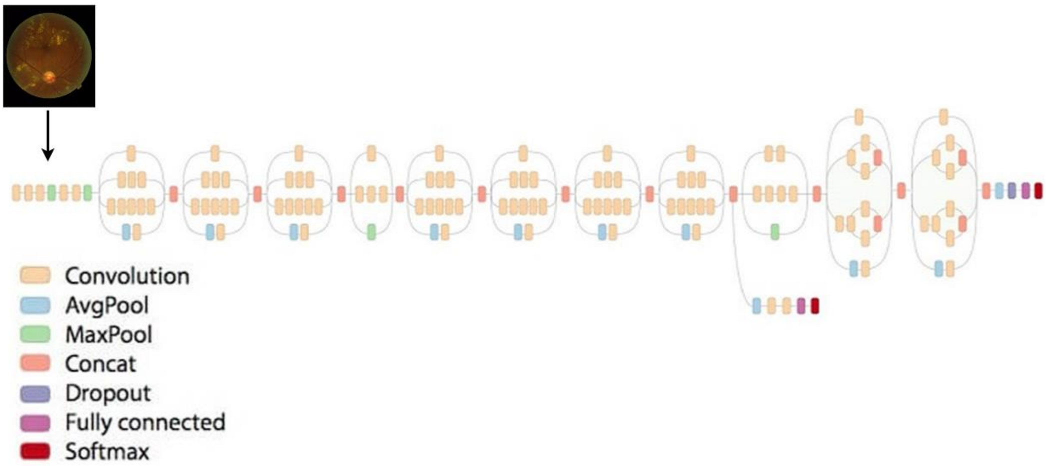



**Fig 3.7.** Architecture of Inception V3

## 3.6 Ablation Study

When creating a unique transfer learning model, the efficiency of the final model is typically improved by the addition of numerous concepts. But it's useful to comprehend the effects of each of these improvements separately in a study. In order to assess the effects of individual components and quantify the performance loss of the entire model, researchers routinely examine their models with each feature disabled. The ablation study to create a more robust model to predict the DR is described at results section.

# CHAPTER 4

# Experimental Results and Discussion

## 4.1 Experimental Setup

In order to test different models and configurations, we used three PCs, each of which has an Intel Core i5-8400 processor, 16 GB of RAM, an NVidia GeForce GTX 1660 GPU, and a 256 GB DDR4 SSD for storage.

## 4.2 Evolution Methods

The evaluation is using the confusion matrix like, accuracy, precision, recall, and F1 score. True positive (TP) values are true in reality. False positives (FP) occur when false results are mislabeled. The third form, false negative (FN), occurs when a correct value is misinterpreted as negative. TN and FN are the fourth and fifth choices. A true negative (TN) is a positive value misidentified as negative. Fourth is true negative (TN) [27].

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$\mathrm{F1\ Score} = 2 \times \frac{\mathrm{precision} \times \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} \tag{4}$$

Some more evalution matrix are false positive rate (FPR), false negative rate (FNR), negative predicted values (NPV), mean absolute error (MAE), root mean squre error (RMSE).

## 4.2 Results and Discussion

This section will go through the results of this paper. First of all, DR dataset is tested though the transfer learning models. The best result between the results of transfer learning models is choosen for as the base model for ablation study. In the Table 4.1

shows the accuracy(training, testing and validation), and loss(train, test and validation) for the five transfer learning models.

**Table 4.1:** Finding the best result  between the Result of Transfer learning model

| **Model** | **Image Size** | **Time (s)** | **epoch** | **Test_Accuracy (%)** | **Test_loss (%)** |
|---|---|---|---|---|---|
| VGG16 | 224x224 | 43 | 200 | 82.42 | 1.2087 |
| VGG19 | 224x224 | 45 | 200 | 78.23 | 2.076 |
| MobileNet | 224x224 | 35 | 200 | 84.81 | 1.0392 |
| **MobileNetV2** | **224x224** | **34** | **200** | **87.22** | **0 9702** |
| InceptionV3 | 224x224 | 39 | 200 | 82.67 | 1.0057 |

From table 4.1 vacancy that five transfer learning models were trained using 24 X 24 image size with various times and the epoch size is 200.  With the same configuration among five transfer learning models MobileNetV2 has performed the best with an accuracy of 87.22%. So, MobileNetV2 is going to be the base model for the further of ablation study.

### 4.2.1 Results of the Ablation study

The accuracy of classification can be increased by changing a number of design elements. The base CNN architecture is modified in a total of six experiments that are conducted as ablation research. Below are the findings of the ablation investigation are shown in table 4.2

**Table 4.2:** Ablation study on MobileNet V2

**Case Study 01:** Changing polling Layer

| Configuration No. | Polling layer types | Epochs x training times | Test_accuracy (%) | Findings |
|---|---|---|---|---|
| **1** | **Flatten** | **200 x 34s** | **88.26%** | **Best Accuracy** |
| **2** | Global Max pooling | **200 x 34s** | 87.22% | Good Accuracy |
| **3** | Global Average pooling | **200 x 34s** | 86.88.% | Good Accuracy |

- **Case Study 1:** Changing polling Layer
  According to case study 1, the flatten layer provides the highest level of accuracy. Additionally, both global averages and global maximums do not provide good accuracy. 88.26% accuracy is obtained when the layer is flattened, while 87.22% and 86.88% accuracy are achieved when the layer is summed up globally.

**Case Study 02:** Changing the batch size

| Configuration No. | Batch size | Epochs x training times | Test_accuracy (%) | Findings |
|---|---|---|---|---|
| 1 | 16 | **200 x 61s** | 89.23.% | Good Accuracy |
| **2** | **32** | **200 x 34s** | **89.87.%** | **Best Accuracy** |
| 3 | 64 | **200 x 28s** | 88.26.% | Good Accuracy |

- **Case Study 2:** Changing the batch size

  Case study two deals with changing the batch size. The most accurate batch size is 32, followed by 64, and 16. When the batch size is 32 the test accuracy is 89.87%.

**Case Study 03:** Changing the Loss Function

| Configuration No. | Loss Functions | Epochs x training times | Test_accuracy (%) | Findings |
|---|---|---|---|---|
| **1** | **Categorical Cross entropy** | **200 x 34s** | **91.51%** | **Best Accuracy** |
| **2** | Mean Squared Errors | **200 x 34s** | 89.87% | Good Accuracy |
| **3** | Mean absolute errors | **200 x 34s** | 90.23.% | Good Accuracy |

- **Case Study 3:** Loss Function change

  As a result of experimenting with different loss functions, case study 3 finds that categorical cross-entropy produces the best results 91.51%.

**Case Study 04:** Changing the Optimizer

| Configuration No. | Optimizers | Epochs x training times | Test_accuracy (%) | Findings |
|---|---|---|---|---|
| **1** | **Adam** | **200 x 34s** | **93.28%** | **Best Accuracy** |
| 2 | Nadam | **200 x 34s** | 92.88.% | Good Accuracy |
| **3** | SGD | **200 x 34s** | 91.51.% | Good Accuracy |

- **Case Study 4:** Optimizer change
  Adam optimizer provides the highest accuracy when compared to Nadam, SGD, and Adamax optimizers in case study 4. The accuracy achieved 93.28%.

**Case Study 05:** Changing the Learning Rate

| Configuration No. | Learning rates | Epochs x training times | Test_accuracy (%) | Findings |
|---|---|---|---|---|
| **1** | 0.01 | **200 x 34s** | 91.8% | Good Accuracy |
| **2** | **0.001** | **200 x 34s** | **93.28.%** | **Best Accuracy** |
| **3** | 0.0001 | **200 x 34s** | 90.27% | Good Accuracy |

- **Case Study 5:** Learning Rate change
  Learning Rate change in comparison to 0.001, 0.0001, and 0.01, when using 0.01 provide the highest accuracy.93.28% is highest achieved by 0.001 learning rate.

**Case Study 06:** Changing Epoch

| Configuration No. | No of Epochs | Epochs x training times | Test_accuracy (%) | Findings |
|---|---|---|---|---|
| **1** | 10 | **10 x 34s** | 69.39% | Poor Accuracy |
| **2** | 50 | **50 x 34s** | **82.57%** | Good Accuracy |
| **3** | 100 | **100x 34s** | **86.14%** | Good Accuracy |
| **4** | **200** | **200 x 34s** | **93.28.%** | **Best Accuracy** |

- **Case Study 6:** Epoch change
  Epoch change in comparison to 10, 50,100 and 200, when using 200 provide the highest accuracy.93.28% is highest achieved by 200 epochs

### 4.2.2 The final configuration of the model

After ablation study, the final configuration of the proposed model is provided in table 4.3

**Table 4.3:** Configuration of the proposed model

| **Configuration** | **Value** |
|---|---|
| Image sizes | 224 x 224 |
| Epochs | 200 |
| Optimization Functions | Adam |
| Learning rates | 0.001 |
| Batch sizes | 32 |
| Activation functions | Softmax |
| Dropouts | 0.5 |
| Momentum | 0.9 |
| Accuracy | 93.28% |

From table 4.3, we can see the final configuration of the proposed model. The Image size is 224 x 224, Epoch size is 200, Optimization Functions is Adam, Learning rate is 0.001, Batch sizes is 32, Activation function is Softmax, Dropout is 0.5, Momentum is 0.9, Finally the achieved accuracy with these configuration is 93.28%.

### 4.2.3 Performance and statistical analysis

As shown in table 4.4, the most hyper-tuned and robust CNN model has the following FPR, FNR, FDR, KC, MCC, MAE, and RMSE.

**Table 4.4:** Statistical analysis of the proposed model

| Statistics | Value (%) |
|---|---|
| Accuracy | 93.28 |
| FPR | 1.81 |
| FNR | 7.29 |
| MAE | 8.42 |
| RMSE | 34.43 |
| Precession | 92.28 |
| Recall | 92.71 |
| F1 Score | 92.49 |
| Specificity | 98.18 |

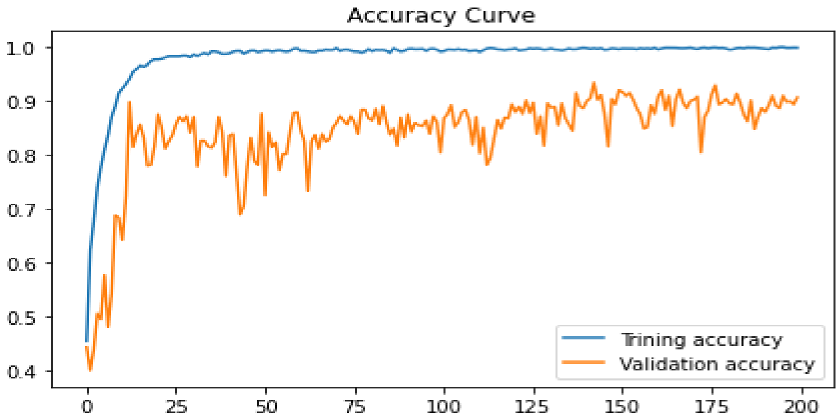
From table 4.4, we can see the performance and statistical analysis of the proposed model. The Accuracy is 93.28%, FPR is 1.81%, FNR is 7.29%, MAE is 8.42%, RMSE is 34.43%, Precession is 92.28%, Recall is 92.71%, F1 Score is 92.49%, and Specificity is 98.18%.

### 4.2.4 Confusion Matrix and Accuracy curve and loss curve

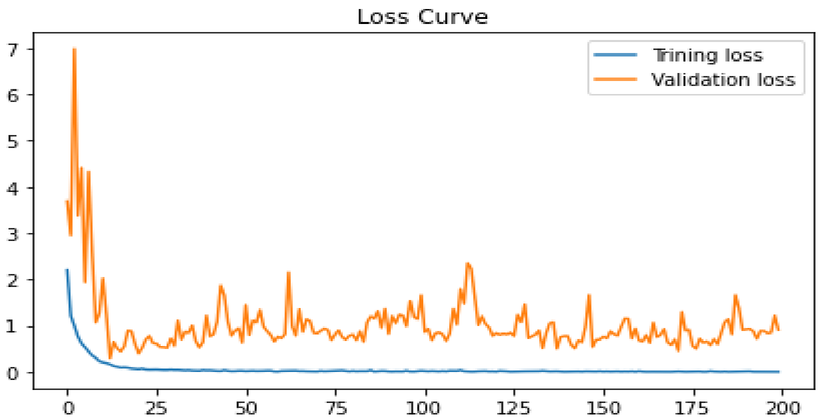
A table describing a classification model's performance on test data with known true values is called a confusion matrix. Performance of algorithms can be shown visually.The confusion matrix is N x N, where N is the total number of target classes. The number of observations that are known to belong to one class but are predicted to belong to another is represented by each matrix item. The confusion matrix provides a summary of the performance of a classification algorithm. The matrix's cells each display the algorithm's success rate.

The rows contain true classes, while the columns contain expected classes. The matrix's top left cell contains true positives, or observations that were correctly classified as members of the target class. False positives,or observations that were incorrectly assigned to the target class, are displayed in the top right cell. False negatives, or observations incorrectly classified as not belonging to the target class, are displayed in the bottom left cell. Real negatives are represented in the bottom right cell of the matrix.

Figure 4.1 shows the accuracy and loss curves and Figure 4.2 shows Confusion matrix for the best-performing model.




(a)




(b)

**Fig 4.1.** Loss and accuracy curve of the model.

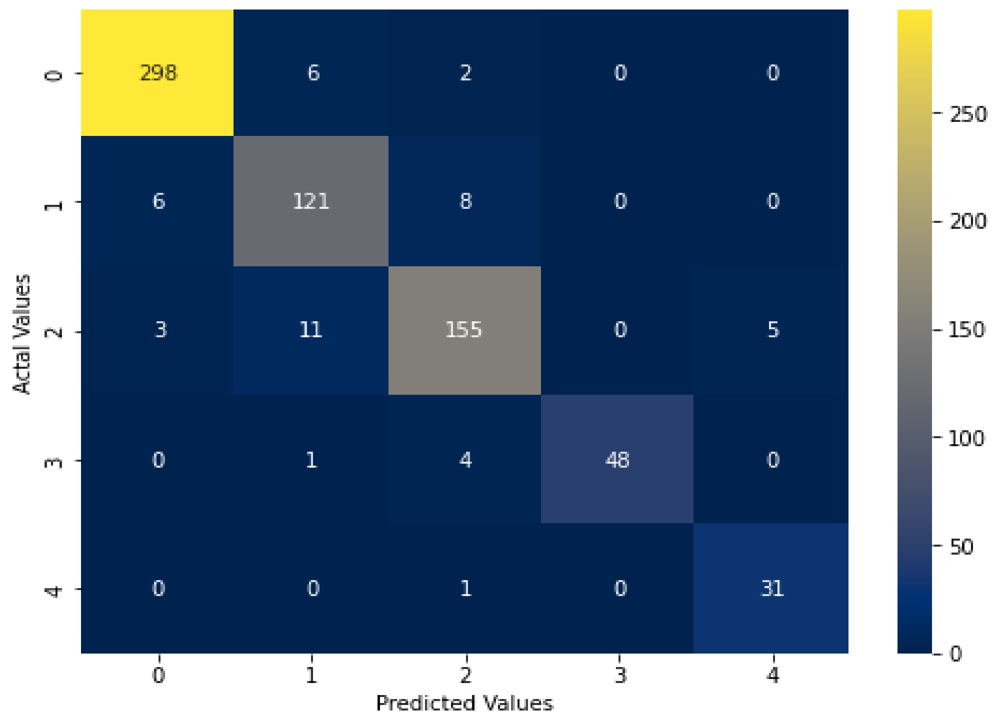



**Fig 4.2**. Confusion Matrix of the proposed model.

### 4.2.5 Model Comparison

Table 4.5 shows the model, time and accuracy comparison with literature review.

**Table 4.5**. Comparison with other literature works.

| Author | Model | Per Epoch Time | Accuracy |
|---|---|---|---|
| Akhilesh et al. [2] | Inception-ResNet-v2 | 53 seconds | 72.33% |
| Borys et al. [10] | Proposed model | 63 seconds | 90.09% |
| Mamta et al. [12] | Proposed CNN model | 47 seconds | 74.40% |
| Daniel et al. [15] | Proposed Deep Learning Approach | 61 seconds | 91.60% |

| | | | |
|---|---|---|---|
| Yashal et al. [16] | Inception V3 | 59 seconds | 89.75% |
| Our proposed Model | Proposed MobileNetV2 | 34 seconds | 93.28% |

Table 4.5 shows the comparison with the other literature works. From here we can see that Akhilesh at al. [2] achieved an accuracy of 72.33% with 53 seconds. From the table it is visible that the accuracy which got over 90% or near 90% accuracy, they have a high per epoch time. So after comparing the result with other studies it is visible that our proposed model achieved best accuracy with less time complexity. Fig. 4.3 shows the accuracy comparison with literature reviews.

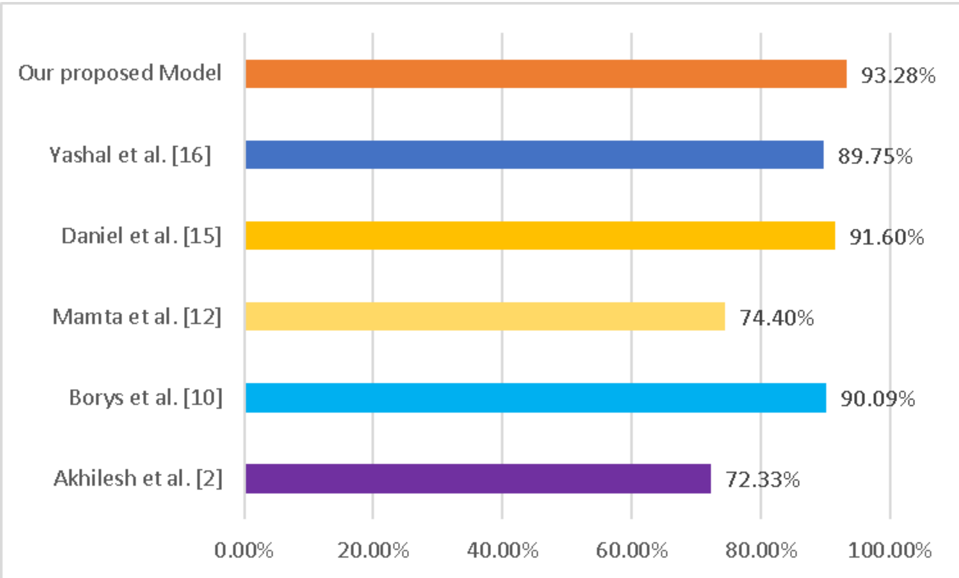



**Fig 4.3**. Accuracy comparison of the proposed model.

# CHAPTER 5

# Impact on Society, Environment and Sustainability

## 5.1 Impact on Society

Diabetic retinopathy is a serious complication of diabetes that can cause vision loss or blindness. Early detection and treatment of diabetic retinopathy can significantly reduce the risk of vision loss and improve the quality of life for people with diabetes.

The benefits of early detection of diabetic retinopathy extend beyond the individual patient and can have a positive impact on society as a whole. Early detection and treatment can help to reduce the burden of disability caused by vision loss due to diabetic retinopathy, which can have significant economic and social consequences.

For example, people with vision loss due to diabetic retinopathy may be unable to work or may require assistance with daily activities, leading to decreased productivity and increased healthcare costs. In addition, early detection and treatment can help to reduce the overall healthcare costs associated with diabetic retinopathy, as early treatment is often more effective and less costly than treatment for advanced stages of the disease.

Overall, early detection of diabetic retinopathy can have a significant positive impact on the lives of people with diabetes and on society as a whole.

## 5.2 Impact on Environment

Using computer vision for the early detection of diabetic retinopathy can potentially have a positive impact on the environment in several ways.

The potential benefit of using computer vision for early detection is that it can make the diagnostic process more accessible and convenient for patients, particularly those in remote or underserved areas. This can help to reduce the need for patients to travel long distances for diagnostic appointments, which can have a positive impact on the environment by reducing transportation-related emissions.

Overall, the use of computer vision for early detection of diabetic retinopathy can have a positive impact on the environment by increasing the efficiency and accessibility of the diagnostic process and reducing the use of certain diagnostic tools and the need for transportation.

## 5.3 Sustainability Plan

Here are some potential components of a sustainability plan for using computer vision for the early detection of diabetic retinopathy:

a) **Energy efficiency**: Ensuring that the computer systems and other equipment used for the diagnostic process are energy efficient can help to reduce the environmental impact of the process.

b) **Use of renewable energy:** Using renewable energy sources, such as solar or wind power, to power the computer systems and equipment used for the diagnostic process can further reduce the environmental impact.

# CHAPTER 6

# Summary, Conclusion and Future Work

## 6.1 Summary of the Paper

This research is proposing a robust CNN model with deep learning that performs ablation studies to categorize DR disease. The disease is colored and the image's overall quality is enhanced by removing artifacts, reducing noise, and enhancing the image. The number of DR illness images has increased as a result of enhancing strategies. The augmented dataset provides a base CNN model initially. Our proposed model, the robust CNN model, was acquired via an ablation investigation. A collection of publicly available images of DR illnesses is utilized to train the algorithm. With an accuracy of 93.28 %, the robust model provided generated the best results. The model is robust and has an outstanding capacity to generalize to new data. In situations involving the detection of binary and multi-class diabetic retinopathy illnesses, the model also achieves a high level of accuracy and recall.

## 6.2 Conclusion

The classification of diabetic retinopathy (DR) illnesses via transfer learning is proposed in this research using a convolutional neural network-based approach. Regardless of whether the diabatic retinopathy is there or not, a technique has been devised that may help both laypeople and medical professionals identify different types of DR. The accuracy of the suggested model was 93.28%. The experimental and assessment phases have led to the conclusion that the model may be used as a reference for medical professionals to use in detecting DR illnesses. By taking a few random images, any doctor may identify the correct findings, but the previous method takes too long to determine whether or not a case has been correctly diagnosed.

## 6.2 Limitation and Future work

In this work, transfer learning models outperformed conventional classifiers in terms of multiclass classification. Despite a significant loss of correct medical data, a fundamental shortcoming in the research, the dataset for the suggested model is insufficient. The effectiveness of the suggested methodology might soon be evaluated using greater amounts of unanalyzed medical photos and real-time medical data. However, the bulk of testing show that the study's proposed model correctly classifies the four different kinds of DR diseases. Although it might have a few minor difficulties, it is not impossible. It is not difficult to guarantee that the suggested fine-tuned MobileNetV2 model is accurate and enhanced in all aspects of diagnosis, notwithstanding a few small shortcomings. This is feasible to achieve. Future research can look at the therapeutic application of deep learning for the diagnosis of other illnesses. Transfer learning could be beneficial for diseases that are rather rare. Additionally, as models mature, fewer preprocessing procedures can be necessary. Further understanding of the reconstruction kernel or image thickness may also help deep learning models perform better**.**

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