CHAPTER 1

INTRODUCTION

1.1 Outline of the study

Research in the healthcare industry is given high priority among scientists and general practitioners to discover novel techniques. Medical imaging is one of the high-priority areas for potential research with computer-aided medical devices, especially for disease diagnostics. Medical experts enhance the lives of people by interpreting the images as novel diseases arise day by day. Diagnosing the disease rapidly, accurately, and economically are the aims of the researchers. The challenges involved in analyzing medical images are the complexity, massive number of images, wide variations in the medical image data and so on. For many real-world applications, deep learning techniques have been applied, and they provide accurate solutions. Hence, in medical imaging, the deep learning architecture optimizes the medical images in image segmentation, classification, and identification of diseases at the early stage.

In this current study, the focus is on the retinal fundus images in classifying the stages of diabetic retinopathy, which aids in the improvement of the decision-making system. Diabetic Retinopathy (DR) is an eye disease that affects the vision of a diabetic patient and can lead to blindness in its advanced stages. The seepage on blood vessels in the retina in diabetic patients is the cause of permanent blindness. The rising number of diabetic patients worldwide is the necessity for emerging techniques by researchers in the present era. Scanning the retinal image to analyze the blood vessel layers at the rear of the eye is performed in retinal biometrics. If DR disease is identified at an initial stage and treated precisely, then eye blindness can be prevented. A digital photograph of a human retina is used for screening patients with DR and Glaucoma diseases. There are few conventional techniques in which the Vessel tracking technique can be applied to extract retinal vessels. Retinal image analysis requires the location of the Optic Disc (OD) to locate the components in the retinal images. The tracking technique uses the location of the retinal image as the reference length for calculating the distances in retinal images. Identifying the location of OD is essential for classifying the stages of DR disease and its pathological structures in retinal images. This process automatically detects the center point of OD.

The abnormal retinal images can be measured with the help of retinal vessel structure that specifies the state of the disease. Hence, a technique to measure the blood vessels is required. An effective tool such as Computer-Aided Design (CAD) aids the ophthalmologist in categorizing normal and abnormal retinal images. Support Vector Machine (SVM), neural network, and K-nearest neighbor (KNN) classifiers are the most common classifiers to categorize the retinal images successfully based on the features set. OD, blood vessel thickness, hard exudates, vein diameter measurement, and hemorrhages are a few of the features extracted from the retinal images for normal and abnormal classification. Finally, the retinal images are graded based on the classification results and the percentage of accuracy, precision, recall and F1-score are identified. The DR images are classified into different stages, such as mild non-proliferative DR, moderate non-proliferative DR, severe non-proliferative DR, and proliferative DR, based on their ophthalmoscopic features. Hence, there is a need for a more accurate DR diagnosis.

The current work focuses on improving the classification performance of Diabetic Retinopathy stages, resulting in more accurate diagnosis. This chapter initiates with a detailed description of the human eye anatomy, a brief of a few diseases triggered in the optic nerve and the optic disc, followed by a detailed explanation of diabetic retinopathy, symptoms, types, and grading of DR. Computer-aided models for DR analysis such as machine learning (ML) and deep learning (DL) models are discussed. The chapter subsequently defines the problem statement and description, research objectives, and contributions. The chapter concludes with the framework of this thesis.

1.2 Human Eye Anatomy

A vital organ in the human body is the eye, which aids in viewing the exterior world and sensing the experience. The light emanating from the surrounding environment is converted into signals that the brain interprets as images. The diverse parts of the eye are shown in Figure 1.1. The light from the external surroundings travels through the eye parts such as the cornea, iris, and lens and touches the retina. The retina with an optic nerve is composed of layers consisting of rods and cones, which are light-sensitive. These rods and cones transmit the optic nerve details, where the brain captures the images. The shape of the eye is spherical with 24 mm diameter consisting of external and subsequent portions.

Lens, cornea, humor, vitreous, and aqueous are refractive media of the eye. The latter of the eyeball is the sclera. The frontal part of the eyeball is the transparent cornea. The posterior portion is the retinal surface. The digital cameras capture the retinal portion, which consists of macula, blood vessels and optic nerve head. The fundus camera captures the retinal surface existing in the latter eye region. The retina image consists of the macula, blood vessels and optic nerve. The glaucoma disease is discovered by investigating the optic nerve region. The optical disc present in the optic nerve head is the fragment present in the fundus image. It is vital to understand the organization of the eye to identify the normal and abnormal retinal images. Figure 1.2 illustrates the fundus image of a human eye with the OD and fovea. The following subsection presents the details of the human eye parts such as the iris, cornea, lens, pupil, vitreous chamber, retina, sclera, optic disc, fovea, and macula.

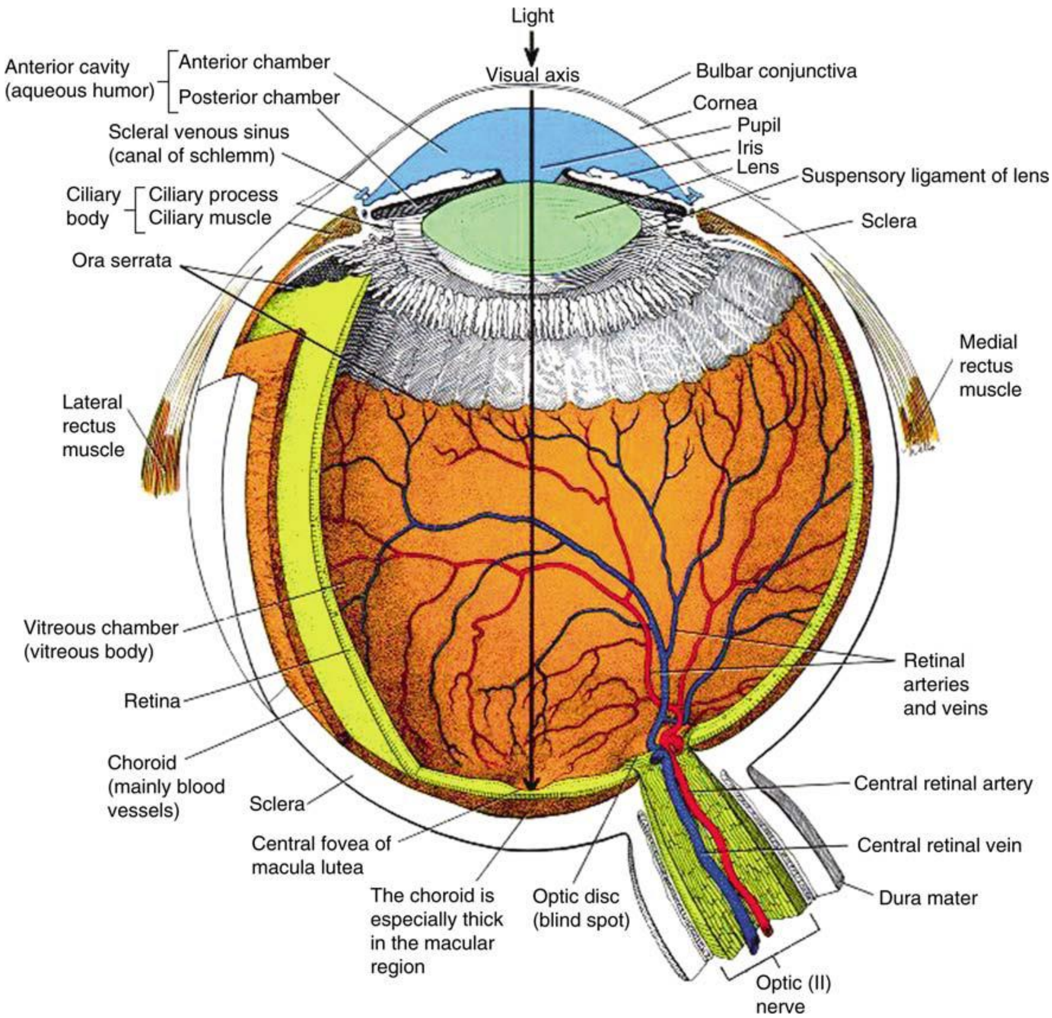

Figure 1.1: Outlook of the human eye (Irsch K *et al.* 2009)

The Iris

It is slender, circular, and pigmented, which handles the light quality entering the eyes. It is the colored area in the eye that can contract and dilate subjected to light intensity. Pupil size is enlarged when enormous light enters, leading to the dilation of pupils.

The Cornea

The transparent area in an eye's anterior region is cornea. The Iris region is protected by altering the light that reaches the eyes. The cornea consists of 78% water, with a vertical size of 11 mm and a horizontal size of 12 mm. The cornea fluid contains watery substance that supply nutrients and oxygen to the eyes. The cornea does not have blood vessels, and it diverts the light. The cornea is 0.5 mm thick and performs 70% of the eye functions. The back of the cornea is the iris with the slender diaphragm. The cornea filters the light and begins to centre the image.

The Lens

It is transparent, biconvex, and located near the cornea. Lens guides the refraction of light on the retina. The lens shape is altered based on the focal distance of the eye.

The Pupil

It looks like a hole in the core of the iris. Pupil regulates the light quantity that enters the eyes by widening the adjacent muscles next to the iris. The pupil absorbs the light with the neighbouring eye tissues and looks black.

The Retina

A slender tissue presents in the optic nerve to receive light from the lens. It collects the light from the lens, transfers it to unbiased signals and finally sends a signal to the brain for visual acknowledgment. The color and light intensity are identified by a photoreceptor cell in the retina. The cell information is transferred through the optic nerve to the brain. The left brain decides the image based on the focus light in the retina. The night vision is captured in black and white rods. The retina receives and processes the light, and in the event of retinal dispassion, it leads to blindness.

The Vitreous Humor

It is the most significant part of the eye present in between the lens and retina. A bright fluid fills the eyeball with 95% of water.

The Sclera

It is the protective and opaque layer of the eyes. It is white with muscles to control eye movement.

The Optic Disc

OD is the blind spot or the optic nerve head. The OD conveys the visual data to the brain with the optic nerve's assistance. Eye components are linked through the optic nerve.

Fovea

It is a tiny and flat area in the latter area of the retina. The fovea is responsible for vision sharpness. It consists of cones to receive visual information. The central region of the macula is the fovea. The shape is altered based on the objects present in different locations. Light-sensitive cells in the fovea are responsible for vision accuracy.

Macula

It is a small, sensitive region in the retina and oval present around the fovea. A pigmented yellow spot is present in the central area of the retina. It handles the broad central vision.

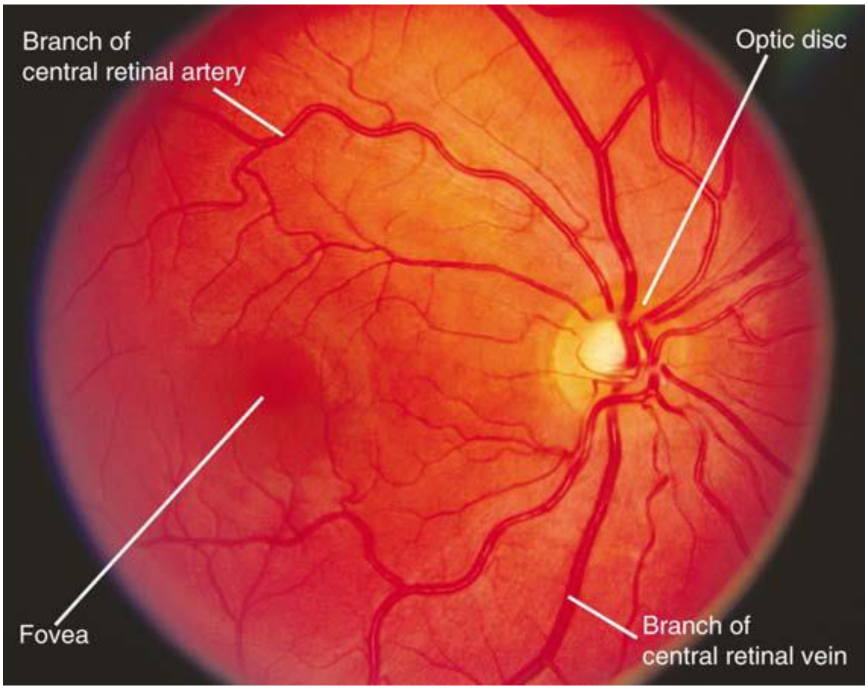

Figure 1.2: Fundus image of the human eye (Irsch K *et al.* 2009)

1.3 Diabetic Retinopathy

This section discusses diabetics, DR, retina condition assessment, retinal fundus images and symptoms of DR, types, and stage classification. Diabetes is a metabolism disorder. In the food digestion process, the necessary energy for the body is attained from glucose. Insulin hormones aid the digested food which arrives in the human body. The problem arises once the pancreas does not create sufficient insulin hormones or when the human body cannot use the insulin hormone effectively. A diabetic person's pancreas either produces insufficient insulin or no insulin. The cells are inefficient in responding to the produced insulin. Hence, there is a considerable amount of glucose in the blood, resulting in diabetics. The disease in the retina is referred to as retinopathy. The light-sensitive cells present in the back of the eyes consist of many retinal blood vessels. An abnormal blood vessel leads to partial vision loss or complete blindness. Retinopathy leads to permanent damage that occurs gradually or suddenly. The blood vessels and nerves are damaged when there is a hike in the blood glucose level, which leads to many diseases; one such disease is DR.

Type 1 and Type 2 are the two types of diabetic classification. The beta cells, which are accountable for the insulin hormone creation in the Type 1 category, are demolished. It prevents the body from creating adequate insulin in the blood, which is termed as an autoimmune ailment. Type 2 is termed as a metabolic ailment, which leads to hyperglycemia. The body becomes inactive during a rise in blood glucose level, which leads to insufficient insulin production. DR disease is acquired from diabetes, which impacts the retinal blood vessels and damages the retina by terminating the oxygen supply to the retina. The risk of bleeding and fluid leakages is increased due to blockages and inconsistent blood vessels. Visual intensity and blurring are the initial signs which lead to glaucoma. DR, glaucoma, optic nerve split, morning glory syndrome, aplasia and hypoplasia are a few of the diseases triggered by optic nerve and optic disc. There are many reasons to reduce visual sharpness, visual impairment, and blindness. This study focuses on classifying the stages of DR disease using Deep Neural Network (DNN) techniques.

DR leads to impaired vision in adults, the changes in the blood vessel structure affect the retinal microvasculature. Examining the retinal blood vessels can help predict diabetes, hypertension, arteriosclerosis, stroke, and cardiovascular disease. For patients with DR, abnormal blood vessels grow on the retinal surface, swelling in blood vessels, and fluid leakage are a few of the symptoms. If these symptoms are unmonitored, it leads to permanent vision loss. The progress of the disease leads to blurred and distorted vision. A group of lesions in the retina of an individual for many years leads to diabetes mellitus. The first stage of DR is managed by maintaining glycemia levels, blood pressure and lipid levels. The second stage is addressed by performing laser treatment to delay the DR progression, and vision loss can be prevented by sealing the blood vessels.

1.3.1 Retina Condition Assessment

Physicians perform specific tests to determine the health of the retinal eye. An ophthalmoscope device effectively examines the retina and other internal parts of an eye. This device is viable for developing related images with varied parts of an eye. This test evaluates the exterior vision region and identifies an area that leads to blind spot development. To examine the blood vessels in the retina, the physicians used fluorescein angiography to induce a vegetable-aided dye into the patient's bloodstream. This process captures continuous eye images rapidly due to the blood circulation in the retina. Fluorescence in angiography is vital to control and treat the disease effectively. To view the rear portion of an eye, an ultrasound scan, which uses high-frequency sound waves, is applied to assess the retinal disorder.

Figure 1.3 illustrates the general fundus eye camera to capture the eye image. Photography methods such as the retina, OD, and macula fundus are applied to visualize vital regions in the internal eyes. This fundus camera identifies the central and exterior areas of the retina along with the white spherical layer inside the retina. It is easy to identify the position and the category of lesions.

Figure 1.3: Fundus Eye Camera

1.3.2 Retinal Fundus Image

The retinal fundus camera captures the retinal fundus image for identifying various kinds of eye infections. The medical professionals capture the retinal image to identify the retinal anomalies. The fundus images consist of features for identifying diseases like DR, glaucoma etc. Retinal image varies for each human eye. Figure 1.4 and Figure 1.5 illustrates the features of retinal image and the retinal image with exudates.

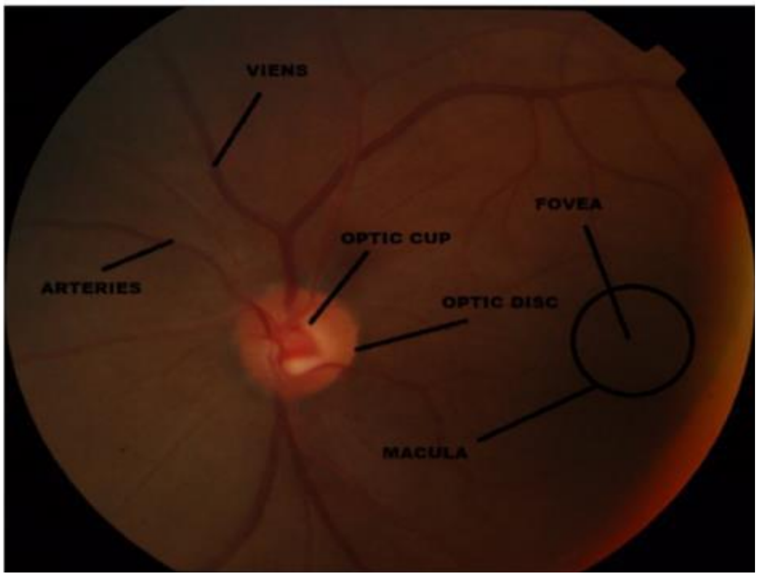

Figure 1.4: Retinal Fundus Image Features

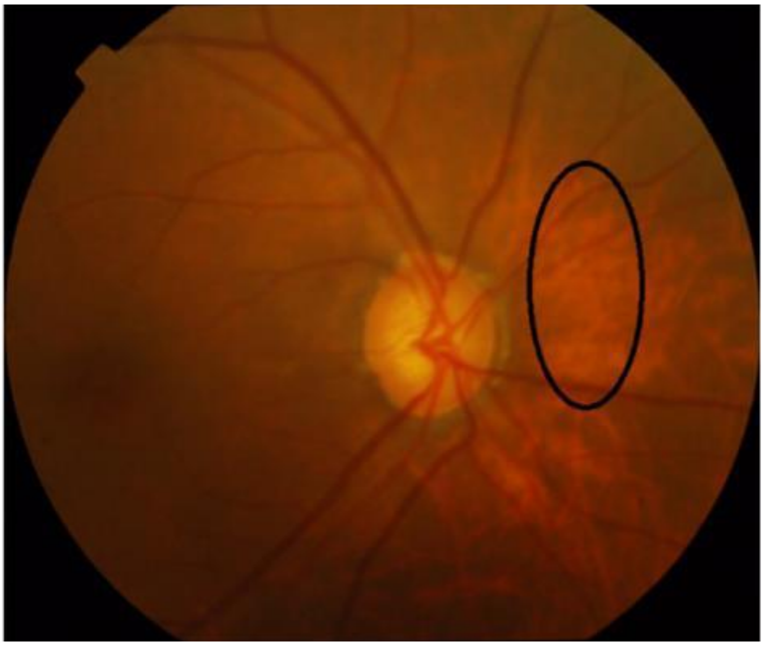

Figure 1.5: Retinal Eye image with Exudates

1.3.3 Symptoms of DR, Types and Grade Classification

The several symptoms of DR are microaneurysms (MA), hemorrhages (HE), hard exudates (EXs), soft exudates (EXs), and Neovascularization. Blur vision, reduced peripheral vision, floaters in vision, color vision problems, and vision adaptation problems are a few of the common problems of DR.

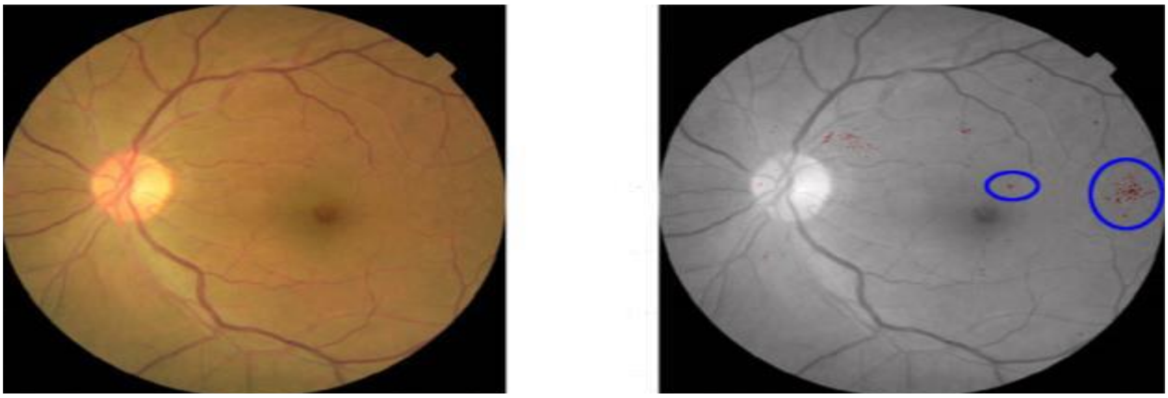

Figure 1.6: Class 1 Sample image

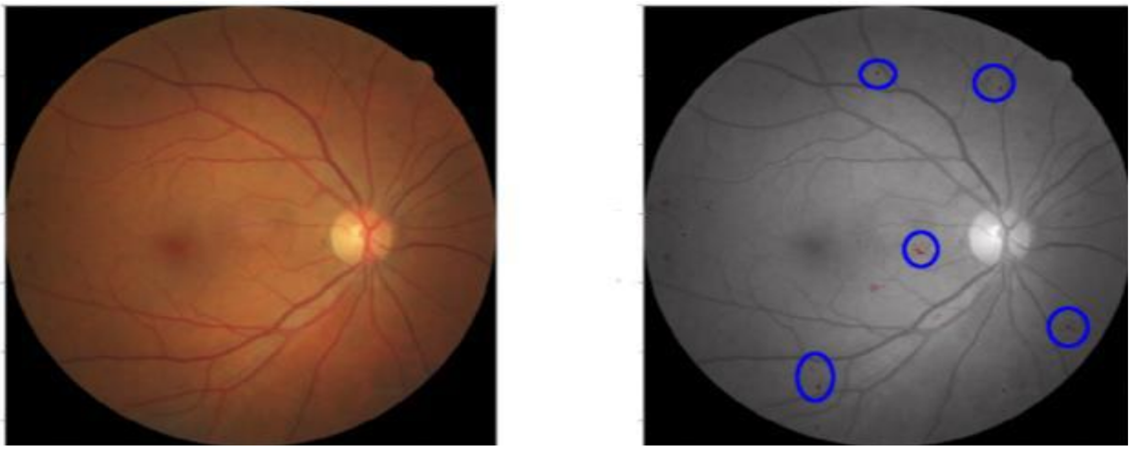

Figure 1.7: Class 2 Sample image

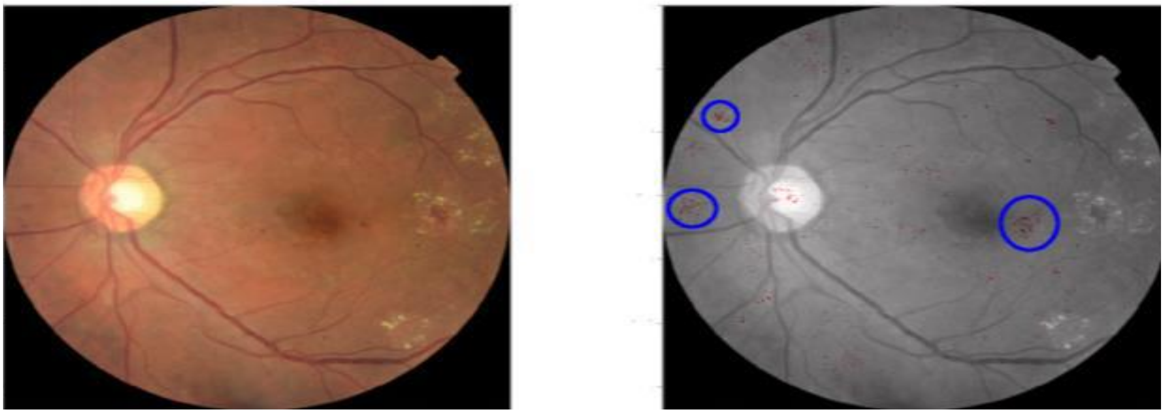

Figure 1.8: Class 3 Sample image

The DR types are non-proliferative DR (NPDR) and proliferative DR (PDR). The grading of DR is categorized as mild NP, moderate NP, severe NP, early proliferative, and high-risk proliferative eye disease. The presence of one microaneurysm across the retinal walls is classified as mild non-proliferative DR. Figure 1.6 shows the class 1 sample image with mild non-proliferative DR. A more significant number of microaneurysm known as capillaries across the retinal walls which interrupt the blood flow and oxygen is classified as moderate non-proliferative.

Figure 1.7 shows the class 2 sample image with moderate non-proliferative. In the severe non-proliferative grade, many blood vessels are affected. There is accumulated damage in the blood vessels, which leads to minimum blood and oxygen flow. When most of the blood vessels in the retina are sealed, it results in blood flow prevention, which leads to the early proliferative stage. Figure 1.8 shows the class 3 sample image with severe non-proliferative. In the neovascularization process, new blood vessels are created to supply blood to the area where the original vessels are sealed. Hemorrhage occurs when there is a leakage of blood in the inner region of the nuclear layer, resulting in high-risk proliferation. Hemorrhage appears circularly in the deep areas of retinal layers.

1.4 Computer-Aided Models for DR Analysis

This section discusses computer-aided models such as machine learning and deep learning for identifying DR disease. The fundus image is processed to predict the level of DR in the evaluation model. The computer-aided evaluation model automatically classifies the healthy and unhealthy fundus images. The model combines feature extraction and classification expertise. Image processing techniques are employed in the Preprocessing phase. Medical image segmentation is automated to understand the anatomical structure. The feature extraction technique eases the classification process to identify the patterns. In this study, ML and DL techniques are applied to categorize the stages of DR automatically affected fundus images.

1.4.1 Machine Learning

A sub-field of artificial intelligence is ML, which consists of machines and procedures that permit the system to train the data without any prominent program. The learning approach is supervised learning, unsupervised learning, and reinforced learning. The training set samples are labeled in a supervised learning procedure. With the help of the existing knowledge, this procedure enabled to learn and normalize the new samples identified. A conditional distribution in probability P (c|X), where c denotes the class to identify, and X denotes the sample. In an unsupervised learning procedure, the complexities in the training set are learned with non-annotated samples. A combined distribution in probability P(X), X represents the sample. The reinforced learning procedure is highly efficient because it collects information from the outside world by gaining new knowledge. A goal-based approach is associated with the environment to enhance efficiency. In the learning-based approach, the strategy for optimizing the hyperparameters consists of a few methods, such as the holdout, k-fold cross-validation and bootstrap methods.

1.4.2 Deep Learning

DL evolves from ML models where the learning data is associated with task-based methods. Optimized solutions for issues related to natural language processing, speech recognition, and image analysis are obtained using DL and Neural Networks (NN) techniques. Deep NN (DNN) and Convolution NN (CNN) are used in the clinical diagnostics domain. The training data count should be high to train the DNN. A minimum number of training images is involved in this study. Hence, data augmentation techniques are employed to enhance the model efficiency. To intensify the dataset and maximize the data variety, an artificial data creation approach is employed in the preprocessing phase. At last, CNN models, which compute based on human brain operations, are developed to accomplish the classification task.

In NN, many interconnected nodes named neurons are computed. In DNN, many hidden layers are situated (Good Fellow *et al.*, 2016). The hidden layer in the network consists of links to the inputs and not the last result. The model consists of input, output, and many hidden layers with few convolutions for calculating and transferring the results to succeeding layers. The CNN layer consists of adaptable weights, biases, and neurons to estimate the product.

Fukushima (1980) projected the initial CNN recognition, but the Backpropagation (BP) model is not applied in the NN training process. CNN trained with BP was proposed by Waibel *et al.* (1989) and is expected to be CNN without pooling. Le Cun *et al.* (1989) came up with an intelligent CNN model using BP technology. CNN model is effectively applied in classification, prediction and detection issues in various domains like natural language processing (NLP), image analysis and speech recognition. CNN model collects the input and alters the hidden layers. It is created using the neuron collection that is linked to the former layer along with the individual layers, which function as autonomous. Figure 1.9 shows the elementary CNN model. The relationship between the channels in convolution layer are the depth of that layers. In the convolution network, the total number of channels must always have the same number of channels as the input. A greater channel depth would lead to the reduction of spatial resolution. The parameters involved are the number of convolution layers, the number of convolution kernels, the number of pooling layers, the number of the fully connected layer and the optimizer.

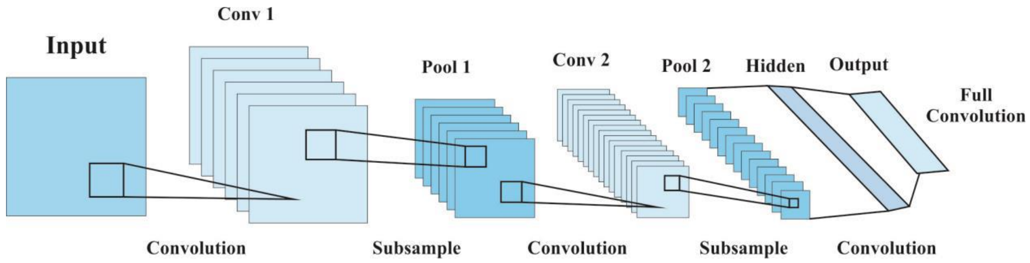

Figure 1.9: Elementary CNN Model

The Fully Connected (FC) layer is called the output layer. The convolutional layer is one of the layers in the CNN structure that processes the results of the neurons. The input image of the local regions is processed by linking the input image with weights and other local regions. Another layer in the CNN structure is the Rectified Linear Unit (ReLU), which is a separate layer. An activation function to improve the nonlinear features of the decision function is the ReLU layer (Krizhevsky *et al.*, 2012). The Batch Normalization (BN) creates surplus and multiplicative artifacts in the hidden units during the training period. The objective of BN is to maximize the optimization. In the max pooling layer, downsampling is estimated in conjunction with the input size's height and width. This layer replaces the existing layer with rectangular region outputs. The FC layer estimates the class scores using NN based on the neurons in the layer, and all the results are linked. CNN alters the actual image from pixel measures for all layers. The SoftMax (SM) layer uses the SoftMax probability distribution function.

The CNN model can be trained from the beginning or through transfer learning. It is tiresome, challenging and time consuming to train the model from the beginning. In certain circumstances accurate results are produced by training the custom model compared to previously trained models. Transfer learning is a previously trained CNN model which is effective with large datasets. A CNN architecture is based on deep learning technique with ImageNet datasets available publicly with weights and kernels. ImageNet database is designed for object discovery and visual recognition researches. Few CNN architectures are LeNet-5, AlexNet, GoogLeNet, VGGNet and ResNet.

1.5 Problem Description

Novel medical imaging techniques, especially in retinal image analysis, aid the ophthalmologist in detecting abnormalities present in the diabetic eye. Computational methods for retinal image analysis are needed to make qualitative assessments in DR disease classification. The identification of DR disease from fundus images requires an automated system to classify and grade the retinal images. Hence, a computerized system to classify the disease stages early through systematic screening is required to provide a more accurate diagnosis.

Problem Statement: The presence of imbalanced classes in the retinal image database and the lack of high-level image features hinder the classification performance of diabetic retinopathy, highlighting the need to address these challenges for significant improvement.

In the context of this research, there are many challenges in the Diabetic Retinopathy Diagnosis System while classifying the stages of DR based on severity levels. Some of them are listed below,

- The accuracy of classifying the DR stages is based on the limited amount of training and testing images.
- Retinal image database consists of imbalanced classes, which degrades the classification accuracy.
- The retinal fundus images with varying levels of noise can have an adverse impact on classification performance.
- Few CNN structures are trained only for image-level supervision. It is challenging to identify soft EXs, hard EXs, MAs and HEs irregular signs.
- Low and mid-level image features may not include all crucial signs such as soft EXs, hard EXs, MAs, and HEs, which are essential to classify the DR levels effectively.
- The efficiency of the classification process depends on RF image resolution. It also relies on hyper-parameters like learning ratio, processing time, number of layers, batch size, and so on.

The limitations and challenges faced in proposing the model are listed below:

- One of the common challenges that most deep learning models encounter is overfitting. However, the proposed SGAN-OECR model does not suffer from overfitting, making it less likely to memorize noise or outliers present in a smaller dataset. The SGAN-OECR model performs well not only on the training data but also on the test data. The Training vs. Test Data Performance Graph is shown in the Annexure section of the thesis.
- Another challenge in deep learning models is the requirement for substantial computational resources, especially for those with complex architectures. Training these models often involves large datasets and intricate network structures, necessitating powerful hardware such as GPUs or TPUs. However, this research successfully manages to optimize the computational resources needed to run the deep learning model efficiently.
- The limitations of the proposed deep learning model include the fact that implementing the model in real-time may not be cost-effective, requires large computational resources, and necessitates a significant amount of labeled data to achieve more accurate results.

The clinical applicability in proposing the model is outlined below:

- Integrating with the existing system is the main challenge where most healthcare facilities rely on electronic health records (EHR) and medical imaging systems. Integrating a new DL diagnostic system with these legacy systems can be technically challenging, requiring significant customization and possibly leading to workflow disruptions.
- Data quality and variability with the real-world clinical data often varies in quality, with inconsistencies such as missing labels, poor image quality, or incomplete patient records.
- Real time processing and infrastructure in diagnostic systems require robust computational infrastructure to process large amounts of data quickly and accurately.
- Cost and resource allocation in implementation of a DL diagnostic system can be costly, requiring investment in technology, training, and ongoing maintenance.

- Patient acceptance and communication can be a real challenge where patients may have concerns about being diagnosed by an artificial intelligence system, particularly if they do not understand how, it works or fear it may replace human judgment.

1.6 Research Objectives

The objectives of this study are listed below.

Primary Objective: To improve the classification performance of DR using an optimized Convolutional Neural Network (CNN) based ensemble classification and regression framework.

Secondary Objectives:

- To develop an image preprocessing framework that eliminates retinal fundus image noises and enhances the image contrast to achieve improved classification performance.
- To deploy augmentation strategies that address class imbalance issues to improve classification performance.
- To enhance CNN architecture that captures subtle diabetic retinopathy image features to improve the classification performance.
- To develop an enhanced optimization technique that searches for the best set of CNN hyper-parameters to improve the classification performance.

1.7 Research Significance

Some of the significant contributions in this research work are discussed in brief.

- Image preprocessing is performed in two stages: denoising and contrast enhancement.
    - Firstly, a hybrid denoising technique for the retinal fundus images is proposed by combining Discrete Wavelet Transform (DWT) and K-Singular Value Decomposition (K-SVD) along with Adaptive Gaussian Thresholding. The proposed DWT_K-SVD method effectively handles Gaussian noise and Salt-and-pepper noise variations commonly found in retinal images and makes it more adaptable to different types of retinal images and various image acquisition conditions, enhancing its generalization to diverse datasets.
    - Secondly, three different image contrast development ways, such as Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast

Limited AHE (CLAHE), are performed on denoised images. CLAHE provides better results in improving image quality and highlighting fine details.

- Image Augmentation strategies on pre-processed retinal images are used to expand the dataset. This mitigates the impact of class imbalance on deficient databases and improves model performance, generalization, robustness, and data diversity.
- An adaptive NN model with Gradient Boosting (GB) named the ResNetGB model is created to integrate with the Multi-Scale Attention (MSA) method to enhance the accuracy of DR stage classification.
- A high-level interpretational space is considered in an encoder system to embed the Retinal Fundus (RF) image, merging the mid and high-level data, thus fortifying the analysis.
- A Multi-Scale Feature Pyramid (MSFP) is constructed to record RF images in different locations.
- The MSA scheme is applied in an interpretational space to enhance the discriminative power of feature analysis.
- A Special Generative Adversarial Network with an Ensemble Classification Regression (SGAN-ECR) model aims to enhance the accuracy of the classification of DR stages. A high-quality RF image is synthesized. Ensemble MSA-ResNet regression and classifications are used to train the model.
- An Optimization method is proposed for choosing optimal hyper-parameters of the MSA-ResNet in the SGAN-ECR. An Enhanced Mine Blast Optimization Algorithm (EMBOA) is proposed. The convolution layers count, filters count, filter size, Fully Connected (FC) layers count, and the hidden units are a few of the hyper-parameters to be optimized. The proposed SGAN-OECR aims to enrich the classification accuracy of DR stages.
- The proposed deep learning models are validated on benchmark datasets: The APTOS 2019 and the Indian Diabetic Retinopathy Image Dataset (IDRiD).

- The proposed models are trained separately using benchmark images and pre-processed images, and their classification performance is evaluated both with and without preprocessing.

1.8 Framework of the Thesis

The framework of the thesis is organized as follows.

In Chapter 1, human eye anatomy, diseases triggered in the optic nerve and the optic disc, diabetic retinopathy, symptoms, types, and grades of DR are discussed. The problem statement and description, research objectives, and contributions are clearly explained.

In Chapter 2, a broad literature review related to the preprocessing phase, DR disease classification and grading methods are discussed.

Chapter 3 describes the outline of the research procedure. The complete process involved in this research work is presented. It briefs the three proposed models of the study. The CNN ResNet-34 structure, system configuration, dataset description, DR severity levels and dataset distribution based on the severity levels are described.

In Chapter 4, the image preprocessing techniques for denoising the image, contrast enhancement, histogram-based image enhancement techniques and augmentation pipeline operations are discussed.

Chapter 5 discusses the proposed ResNetGB model along with the MSA strategies to enhance the classification performance of DR stages.

Chapter 6 discusses the proposed SGAN-ECR model for high-quality image creation. A detailed ensemble classification and regression model for DR stage classification is described in detail.

Chapter 7 discusses the proposed SGAN-OECR model for optimizing the hyperparameters to improve the classification performance. A detailed ensemble classification and regression model, along with the optimization algorithm for parameter tuning and DR stage classification, are discussed.

In Chapter 8, the conclusion of the study and suggestions for future enhancements are discussed.

1.9 Summary

This chapter briefs about the outline of the study illustrates human eye anatomy along with an explanation of the various parts of the eye such as the cornea, iris, pupil, lens, vitreous chamber, sclera, optic disc, retina, macula, and fovea. A brief description of diabetics and diabetic retinopathy diseases is given. The symptoms, types and stages of DR disease are described. Computer-aided models for DR analysis, such as ML and DL models, are described. The problem description section describes the problem statement and definition. The research objectives and significance are elaborated. Finally, the framework of the thesis is presented.