COMPREHENSIVE STUDY ON OPTIMIZED PREPROCESSING FOR DIABETIC RETINOPATHY CLASSIFICATION USING ENSEMBLE DEEP LEARNING MODEL

A PROJECT REPORT

Submitted by

PRERANA BORA

(En. No.: MSAI22R013)

in partial fulfillment for the award of the degree

of

MASTER OF SCIENCE

IN

COMPUTER SCIENCE (AI&ML)

DEPARTMENT OF COMPUTER SCIENCE (AI&ML)

RAJIV GANDHI NATIONAL INSTITUTE OF YOUTH DEVELOPMENT

SRIPERUMBUDUR- 602105

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BONAFIDE CERTIFICATE

Certified that this Project report "**Comprehensive Study on Optimized Preprocessing for Diabetic Retinopathy Classification using Ensemble Deep Learning Model "** is the bonafide work of **Prerana Bora** who carried out the project work under my supervision.

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DECLARATION

I, **PRERANA BORA (MSAI22R013)** do hereby declare that the project entitled "**Comprehensive Study on Optimized Preprocessing for Diabetic Retinopathy Classification using Ensemble Deep Learning Model ”** is the record of the original work carried out by me and that it has not formed the basis for the award of any degree, diploma, associate ship or fellowship.

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From
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To
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Dear Prerana,

I hope this letter finds you well. I am pleased to offer you an internship opportunity in the Department of Engineering Design at IIT Madras, under the supervision of Prof. Ganapathy Krishnamurthi. This internship is a valuable opportunity to gain practical experience in the field of engineering design and contribute to cutting-edge research projects.

The internship is scheduled to begin on 04/03/2024 and end on 11/06/2024. During this time, you will have the opportunity to work on medical image analysis related projects.

We look forward to welcoming you to IIT Madras and are excited to work with you on this project.

Sincerely,

Ganapathy Krishnamurthi

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I extend my heartfelt thanks to everyone who has supported me throughout my internship focused on ”Comprehensive Study on Optimized Preprocessing for Diabetic Retinopathy Classification Using Ensemble Deep Learning Models.”

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Lastly, I acknowledge and commend myself for the dedication, perseverance, and resilience that have enabled me to overcome obstacles and achieve milestones in this internship.

Together, your collective support and encouragement have been integral to the successful completion of this internship.

Prerana Bora

ABSTRACT

Diabetic retinopathy (DR) is a leading cause of blindness among adults, making its early detection crucial for effective treatment and vision preservation. This study explores the impact of different preprocessing techniques on the performance of an ensemble deep learning model for DR detection. We evaluated three preprocessing strategies: CLAHE, Ben Graham's method, and a Modified approach that integrates features of both techniques.

CLAHE preprocessing enhances image contrast, making subtle features more visible, which is critical for detecting the fine details indicative of DR. On the other hand, Ben Graham's method focuses on edge enhancement and standardizing image size, which aids in maintaining consistency across different images and improving model performance.

Recognizing the strengths of both methods, we developed a Modified preprocessing strategy aimed at bridging the gap between contrast enhancement and size standardization. This hybrid approach seeks to balance the advantages of both CLAHE and Ben Graham's methods, potentially offering a more comprehensive solution for preprocessing in DR detection tasks.

The ensemble model employed in our study combines the architectures of Inception V3, ResNet50, EfficientNetB5, and DenseNet169. By leveraging the diverse feature extraction capabilities of these models, we aim to improve the robustness and accuracy of DR detection. The use of an ensemble model allows for integrating multiple perspectives, which is particularly beneficial in medical image analysis where capturing various aspects of the data is critical for accurate diagnosis.

In this study, we provide a comprehensive evaluation of the effects of different preprocessing techniques on the performance of our ensemble model. Our findings highlight the importance of selecting appropriate preprocessing methods to enhance the efficacy of deep learning models in medical imaging. Future research should continue to refine these preprocessing strategies to further improve the reliability and accuracy of DR detection, ultimately contributing to better patient outcomes.

Keywords: Diabetic Retinopathy, CLAHE, Ben Graham's, Ensemble Model, InceptionV3, ResNet50, EfficientNetB5, DenseNet169, Deep Learning

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Acronyms

DR	Diabetic Retinopathy
BM	Base model
CLAHE	Contrast Limited Adaptive Histogram Equalisation
ROC	Receiver Operating Characteristic Curve
DL	Deep Learning
ML	Machine Learning

Symbols

Π An Pi Symbol
β An Beta Symbol
σ An Sigma Symbol
α Another Alpha Symbol

Chapter 1

Introduction

Diabetic retinopathy is one of the major complications that can arise in diabetes mellitus (DM). Currently, there are about 425 million people worldwide suffering from diabetes and this number keeps on growing at an alarming rate. It is expected to be 592 million by 2035. The research reveals that approximately a third of all diabetic patients will develop DR, while VTDR will occur in nearly one-tenth of diabetic patients. Diabetic retinopathy has become the prime reason for blindness among adults globally. Several diagnostic challenges have emerged as a result of the increased number of DR screenings: (1) There is a huge amount of image analysis tasks which cause significant pressure on physicians; (2) As a result, doctors are unable to give immediate feedback to patients; (3) High-quality medical resources being used up leads to increase in missed or wrong diagnoses. Therefore, early diagnosis for DR faces severe setbacks.

Based on the requirements of the IFDI, the international DR diagnostic standard has provided a universal criterion and basis for the establishment of intelligent DR diagnostic systems. Thus, it is being established as an important area to work with both for the researchers and the businesses. This way constant fine tuning has made it possible to attain the optimizing state of art performance for DR Intelligent Diagnostic Systems. In addition to to generating an output that indicates the presence of DR, the proposed images can categorize the degree and grade of the lesion and distinguish between various pathological morphology in different parts of the retina adding to the process of interpretability of the automated system. Hence, they pointed out that DR diagnostic systems can entitle the generation of the final decisions for diagnostic help to doctors but not for definite diagnosis of patients; in any case, containing definitive diagnostic data, they offer additional data such as diagnostic foundations. Thus, they highlighted that DR diagnostic systems can involve the generation of the final decisions only for diagnostic support to doctors but not for definite diagnosis for patients; in addition to the general diagnostic decision, they also provide more specific information such as diagnostic bases. [1]

In recent years Deep learning has achieved exceptional advancement in computer vision, which has fuelled its development in the medical image diagnosis area. The new trend of utilizing deep learning techniques in medical imaging has developed a significant research direction. In many cases, algorithms based on deep learning have achieved an accuracy level comparable to the physical diagnosis by medical professionals, such as brain tumor diagnosis, breast lesions detection, dermatitis identification, and more. Recently, it has made a huge impact on the disease grading of diabetic retinopathy (DR). Deep learning-based tools have revolutionized the diagnosis mechanism giving a new and advanced approach for DR diagnosis.

The primary contributions of this project work are as follows: a comprehensive review of the application of deep learning methods in diabetic retinopathy diagnosis. This involves investigating efficient ways to utilize deep learning techniques that yield better classification accuracy, which eventually helps in the early detection of DR in patients, thereby aiding better treatment planning and a better cure rate.

Additionally, by reviewing the past work, and analyzing the scope and limitations in the field of DR grading the thesis work completes the discipline Researchers and clinicians can improve patient outcomes by remaining up to date on these innovative advances, which will keep them informed about the best practices and approaches for precisely diagnosing and grading diabetic retinopathy. The study also compares and contrasts different implementation strategies, analyzing the benefits and drawbacks of each. This comparative study will serve as a resource for the researchers helping them choose the best strategy for their unique research.

By exploring these important topics, the thesis work offers a thorough summary of the state of research, potential paths, and difficulties in the diagnosis of diabetic retinopathy. This information is crucial for directing future studies and expediting the conversion of research results into practical applications, which will eventually help patients by facilitating earlier diagnosis and better treatment of diabetic retinopathy.

1.1 Pathology and Diagnostic Standards of Diabetic Retinopathy

If left untreated, in different stages of the disease, diabetic retinopathy shows a range of clinical symptoms. One such common symptom often found in DR patients is the formation of microaneurysms, or microscopic bulges, in the retinal arteries. These microaneurysms lead to

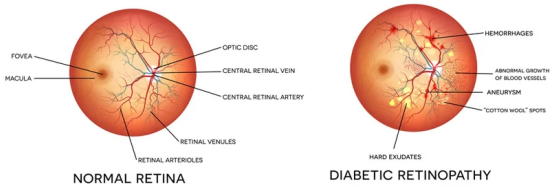

Figure 1.1: Enter Caption

leaks in the retinal vasculature and cause damage to the retina. Retinal hemorrhages are another common feature found in affective retinas. These hemorrhages seep into surrounding retinal tissue and rupture the delicate blood vessels. As stated by Cheung et al. (2010) the size and severity of the hemorrhages can vary in different ranges from small size, localised bleeds to larger and more severe bleeding areas. Exudates are another common feature exhibited by the affective retina. Exudates are lipids and proteins. It seeps out of the microaneurysms and that results in dilated capillaries in the retina. When these materials build up in the subretinal region and outer retinal layer, it damage that discrete area called Hard exudates. These hard exudates are usually well-defined structures and are diagnosed easily by fundoscopic inspection as yellow or white deposits. There exists also soft exudates-which differ in appearance from the hard ones. These are fuzzy-edged, varying-sized, cotton-wool-like, or fluffy patches in the retina with an uneven form. These exudates result from axoplasmic debris and lipid accumulation These microaneurysms, hemorrhages, and exudates are significant identification metrics for clinical diagnosis of DR grading. This indicates the necessity of quick management and routine retinal exams to avoid vision-threatening consequences. [2]

Considering these characteristics in terms of severity Two groups of diabetic retinopathy are distinguished: Non-Proliferative diabetic retinopathy (NPDR): NPDR is the initial phase of DR. Determining the proper intervals for follow-up exams and the likelihood that the illness will progress and cause vision loss depend on the diagnosis of non-proliferative diabetic retinopathy (NPDR). Proliferative Diabetic Retinopathy (PDR): The more severe form of diabetic retinopathy, known as proliferative diabetic retinopathy (PDR), is marked by widespread retinal ischemia and capillary blockage, which trigger a vascular growth response.

The standard system to evaluate diabetic retinopathy is the International Classification of Diabetic Retinopathy which divides the disease into 5 stages based on of the progression status of the disease.

Stage I of diabetic retinopathy, or no apparent retinopathy: First stage of DR, there are no severe signs of retinopathy. It is the early stage of the Damage.

Stage II (Mild NPDR) of the disease is characterised by microaneurysms, which are microscopic bulges in the retinal blood vessels that may leak fluid into the retina.

The third stage (moderate NPDR) is characterised by an increase in the quantity and intensity of microaneurysms and haemorrhages. Certain parts of the retina receive less blood supply when certain retinal blood arteries become clogged.

Stage IV (Severe NPDR): Significant retinal ischemia (lack of oxygen) results from more blood vessels becoming clogged. The body receives instructions from the retina to produce new blood vessels in order to sustain itself.

According to the British Diabetic Association, diabetic retinopathy (DR) is a consequence of diabetes that damages the retinal blood vessels and can cause the following problems:

Regression and Alterations: Macular edema, which causes vision loss and may eventually result in blindness, is caused by the regression of retinal blood vessels, alterations in intravascular components, and increased vascular permeability.

Neovascularization: Proliferative diabetic retinopathy (PDR), characterized by the growth of new blood vessels and fibrous tissues, can result in hemorrhaging and scarring that can lead to blindness.

1.2 Frequency and Global Impacts

DR affects nearly all type 1 diabetes patients and approximately 77% of type 2 diabetics who have had the condition for more than 20 years. It is the major cause of new cases of blindness in developed countries and the most common cause of blindness in middle-income countries. The World Health Organisation estimates that diabetic retinopathy (DR) accounts for 4.8% of the 37 million incidents of blindness that occur globally.

[3]Joanne et al. (2012) conducted a thorough analysis that included 35 research (1980-2008) with 22,896 diabetic subjects. The findings showed: 34.6% of people overall have DR. Where, 6.96% of DRs are proliferative, Eye edema: 6.8 1%, Disability-related vision impairment: 10.2% This corresponds to roughly 93 million individuals suffering from DR, 17 million from prolif-

erative DR, 21 million from macular edema, and 28 million from vision impairment.

1.3 Challenges & Motivation

Diabetic retinopathy (DR) remains a major burden to health systems globally, particularly in the majority of diabetic endemic countries where human resources are scarce. A developing country like India with a huge population of 1.4 billion where 27.4% of the population lives under below the poverty line. In recent times the Indian population has been greatly affected by diabetes, almost 11.4% of the country's population is living with diabetes. So to deal with this huge number we're constantly in need of implementing advanced technology in the healthcare system.

Classification of diabetic retinopathy (DR) into its five different grades; No DR, Mild NPDR, Moderate NPDR, Severe NPDR, Proliferative DR is a tiresome affair. Each of the vascular abnormalities like, microaneurysms hemorrhages, and neovascularization are features that have relatively fine gradations and are best spotted by trained ophthalmologists that can differ significantly between observers. Such subjectivity may result in differential diagnosis and possible commencement of therapy and, hence, patient outcomes are affected. As the number of patients with diabetes increases, the technique of manual grading is neither efficient enough to accommodate the need nor practical, particularly in settings of poor financial status.

AI and deep learning implementation in diabetic retinopathy diagnosis can revolutionize the diagnosis quality of the healthcare system. The idea to adopting deep learning models in diagnosis is inspired by the challenges faced by manual diagnosis, which can be resolved by incorporating these models into diagnosis. In rescue convolution neural network shows an impressive result. Convolutional neural network is a subfield of artificial intelligence. This neural network uses massive amounts of picture data to train classifiers to find relevant features in medical images. Deep learning models incorporating CNN can therefore be used to treat the classification of diabetic retinopathy and thereby provide accurate and reliable functions for the diabetic retinal images. With the use of this technology, the increasing patient population and the scarcity of ophthalmologists can be tackled, also offering numerous important advantages discussed below:
Implementing AI and deep learning techniques to the manual diagnosis enhanced the efficiency and accuracy. The particular models of deep learning can learn and classify the retinal images at far higher speeds and performance compared to the traditional methods. These performances

in effect mean quicker diagnostic tests hence reducing the time that patients have to spend at the hospital while ophthalmologists can dedicate their time to those patients who need more exhaustive analysis and treatment.

AI also helps decrease working load for an ophthalmologist as it screens and/or grades the diabetic retinopathy at first instance. This also helps to reduce the working load, and, most importantly, eliminates the likelihood of human error, thereby producing highly accurate and notably uniform diagnostics.

Early Detection and treatment is one of the major strengths of using AI especially in diagnosing diabetic retinopathy because some of these initial signs may not easily be noticed when the doctor is physically examining the eyes in the initial stage. Fast diagnosis is important since if the condition worsen to the severe stages, the patient is likely going to lose his or her sight. They can be given treatment that entails solutions to their problem before the situation gets worse, risking their vision and facing more complications to their health.

However, there is a challenge to tackle, AI-based diagnostic tools could be significantly costly for healthcare systems if employed. Through limiting several or consecutive diagnostic actions AI could contribute to the decrease of the general healthcare expenditures. Moreover, the intervention at the initial stages may reduce the risk of expensive complications that are characteristic of the later stages of the disease among patients with DR.

AI and deep learning together provide an innovative approach to prevent this common and crippling condition in the physical diagnosis of diabetic retinopathy. If we look at the statistics, in India the ratio of DR patient to ophthalmologist can approximately reach to 928:1, that is for each 928 patients there is 1 ophthalmologist. This indicates an urgent need to use advanced technology to support physical diagnosis of doctors, which in turn improve the speed of diagnosis, accuracy and consistency of the diagnosis. Manual diagnosis often inconsistency found among expert's opinions so there is a need for cross-checking, which results in delay and impacts the accuracy of the result. This is not the scene of the automatic system. By implementing AI and deep learning technology it will be easy to prevent diseases and excel in the healthcare system.

The new trend in healthcare industry is to implementing cutting-edge technology of artificial intelligence and its subfields. To deal with enormous data sets, and complex patterns innovative approach of artificial intelligence (AI) is becoming more and more common . There are three

primary approaches : the symbolic approach to use a rule-based search engine to produce answers; the Bayesian approach, based on the Bayesian theorem; and Deep neural network (DNN) based approach which is the connectionism approach, receiving a lot of attention for its ability to solve complex problems. A branch of artificial intelligence called machine learning (ML) uses data to accomplish Tasks like segmentation, detection, regression, and classification can be accomplished by implementing machine learning algorithm with little to no human intervention. ML comes in the area of nonsymbolic AI. It is data-driven and can make predictions based on data that hasn't been provided yet. The ML model explores the given dataset and learns features from the dataset, on validation dataset it validate these learnt features, and verifies accuracy. machine learning tasks generally split the dataset into training, validation, and test datasets. Artificial neural network which is kind of a artificial prototype of human neural system consists of Input, hidden, and output layers. Weights of the layers are optimised by gradient boosting approach in training to increase the accuracy. But there is a drawback of ANN that they can overfit to trained data and converge to local minima. Deep neural networks are upgraded versions of ANNs. To overcome the drawbacks faced by simple ANNs, Deep learning networks are created by stacking a numerous hidden layer one above another. This allows us to handle complex patterns. In prediction tasks like regression and classification Deep learning outperforms shallow networks. The common drawbacks like overfitting and convergence to minima are handle by using strategies like residual networks and constrained Boltzmann machines. In medical imaging task DNN are commonly used to support radiologists diagnose patients by identifying the abnormalities form medical images of patients. By using DNN experts reached a high accuracy and fast diagnosis. Earlier Computer aided detection (CAD) system was used but it used to generated high false positives and needed to improve.

There are two types of machine learning algorithm : Supervised and Unsupervised. Supervised learning deals with the continuous data and determines the mathematical relationships between inputs and labelled outputs, whereas unsupervised learning learns the hidden patterns in catagorical data. Supervised learning is used for regression tasks in the medical field such as calculating BMI, cholesterol level, sugar level etc. Unsupervised model like SVM, Random forest, and neural networks are used in classification tasks like diabetic retinopathy detection, tumor detection, etc.

Convolutional neural networks are especially good for computer vision tasks. CNN have convolutional layers, pooling layers and fully connected layers which together performs the mapping of features. For tasks like segmentation, classification, object detection CNNs are often preferred because of its high accuracy and ease of handling. But drawbacks faced by CNN is they need a huge number of dataset. Before feeding to the model some common augmentation tasks are

applied to the images like rotation, cropping, scaling, shifting, etc.

DNNs are prevalently used in radiological tasks like Diabetic retinopathy diagnosis and tuberculosis, tumour detection etc. For performance enhancement of model's experts generally use transfer learning techniques and to deal with the data scarcity advanced techniques like generative adversarial networks makes its place in the medical imaging tasks. Deep learning and machine learning have become an important area in medical imaging, helping radiologists provide more accurate diagnoses.

1.4 Objectives

The main goal of this project work is to develop an advanced computer program called deep learning models. These programs will learn to recognize hidden patterns in the eye images and grade the input fundus images as their respective stages of diabetic retinopathy. To facilitate prompt medical attention an accurate classification is crucial. The model learns hidden patterns from a large set of pre-labeled fundus images . Those patterns include blood spots, swelling, and abnormal blood vessel growth. It aims to cut down the diagnosis time. It will support doctors to rapidly screen a large number of patient's eyes and detecting the effected one among the all to give immediate attention to the needed ones. In a country like India, with a high volume of patients, implementing AI technology will enhance the efficiency of the healthcare system. This will ensure that more patients receive timely care.

More than two third of the Indian population, in numbers approximately 833 million resides in the rural area. So the project target is to reach those areas where there's a scarce of opthalmologist like unprivileged areas. By implementing this technology to those isolated areas, the people will get an automatic screening of their eyes and get an idea of their eye conditions.

One of the main goal of this project is to make the Diabetic retinopathy screening affordable and time efficient. In physical diagnosis, the experts have to manually distinguish different pathological morphology , which requires a lots of time and also asks for different opinions of experts. Which may cause inconsistent results , so automatic diagnosis will standardize the decision making process. It will help the doctors in decision making by providing understandable interpretation of the eye fundus images. For less experienced practitioners this model will be particularly helpful. This project work tries to tackle those drawbacks of manual diagnosis like

cost and latency.

The project aims to close the gap between the demography of the patient and the opthalmologist's availability. By standardizing the decision-making process helps in taking decisions from inconsistent diagnoses. This automatic diagnosis will support the less experiences ophthalmologists with better interpretation.

This project investigates different preprocessing methods to handle specially eye fundus images for Diabetic retinopathy disease classification. Preprocessing is an essential step to improve input image quality and make it more accessible for the model to handle it. This project explores some popular preprocessing techniques for DR images like CLAHE (Contrast Limited Adaptive Histogram Equalization), Ben Graham's preprocessing techniques, and normal preprocessing techniques and tries to come up with an effective approach for detecting grade 2, grade 3, and grade 4 images. In this project, Ensemble Learning, a Transfer Learning technique is chosen as the base algorithm for the model. To improve the efficiency of the over-all model transfer learning entails employing different pre trained model like VGG, Inception, ResNet, and come up with a combined model which will have qualities of all participated models. By fine tuning the final model for the Diabetic retinopathy classification the performance of the model is increased. In this project, a comparative study of various preprocessing techniques is performed. Using metrics like accuracy, precision, recall, F1 score the model are evaluated trained with different preprocessing techniques and comes up with the more efficient preprocessing technique.

By ensuring these goals the project hopes to develop a robust, reliable, affordable and accessible screening for diabetic retinopathy. This tool will help the medical industry by ensuring prompt diagnosis. In this project, a comparative study of various preprocessing techniques is performed. Using metrics like accuracy, precision, recall, F1 score the model are evaluated trained with different preprocessing techniques.

By ensuring these goals the project hopes to develop a robust, reliable, affordable and accessible screening for diabetic retinopathy. This tool will help the medical industry by ensuring prompt diagnosis.

Chapter 2

Literature Review

2.1 Overview of Traditional Methods

Diabetic retinopathy primarily diagnosed with the traditional methods . These traditional methods involves clinical eye screening by ophthalmologist. By comprehensive detailed eye exam ophthalmologist get a detailed view of eye fundus. In dilated eye exam doctors use a mydriatic eye drops on eye which widen the pupil and give a clear view of the eye retina and the internal morphology. Through visual acuity testing doctor assess how well the eye can see at various distance . Ophthalmoscopy, also known as funduscopy, is a conventional clinical procedure for identifying diabetic retinopathy (DR) since it allows for a direct and thorough examination of the retina and back of it. This procedure uses an ophthalmoscope, a device with a light source and magnifying lenses, to see the eye's internal surface, which includes the retina, optic disc, macula, and retinal vessels. During the process, the patient's pupils are often dilated with pharmacological drugs such tropicamide or phenylephrine to improve visibility. This dilatation enables for a detailed examination of the retinal structure. The ophthalmologist checks the retina for DR-specific symptoms such as microaneurysms, dot and blot haemorrhages, hard exudates, cotton wool patches, and neovascularization. Another diluted eye exam is tonometry. Tonometry measures the intraocular pressure (IOP) to help detect glaucoma, a condition develop by the diabetics. Elevated IOP levels may suggest the presence of glaucoma which may cause for vision loss. If more precise diagnosis is required doctors performs Optical coherence tomography (OCT). This test uses light waves to create cross sectional images of retina. This diagnosis detects any fluid formation in the retina. That indicates the presence of endoema, a condition caused by Diabetics. Another clinical diagnosis process involves injecting a fluorescent dye into the circulation and taking photographs of the retina while it circulates through retinal blood vessels. This diagnosis is called Fluorescein angiography. This test performs well in detecting leaking blood vessels of eye retina.

Fundus photography is used to track any disease development on eye. Fundus photography provides a detailed morphology of the eye retina. These regular eye diagnosis are essential to diagnose diabetic retinopathy and provides patients with proper treatment.

There are several limitations to traditional approaches that can impact their effectiveness in certain situation. Traditional method such as ophthalmoscopy and tonometry rely on the expertise and the experience of the examiner. Manual diagnosis often faces inconsistency in expert's diagnoses, potentially affects the accuracy of result. manual diagnosis may not always detect minor abnormalities of eye fundus, particularly early stages of diabetic retinopathy. This leads to undetected or late diagnoses, when treatment may not be as effective as before. Test such as fluorescein angiography requires injecting fluorescent dye into the eye blood vessel, which may cause some side effects. Manual diagnosis requires a vast amount of time and manpower. Some diagnosis tests like OCT, Fluorescein are may not be readily available in healthcare settings. These tests are also cost-intensive to perform.

2.2 Computer Aided Diagnosis(CAD):

Computer-aided diagnosis (CAD) systems offer an impressive result in diabetic retinopathy diagnosis. These approaches leverage advanced image acquisition techniques, machine learning algorithms, and artificial intelligence to improve the efficiency, accuracy, and accessibility of DR screening and diagnosis. The CAD process first involves image acquisition. It utilizes various imaging techniques, such as fundus photography, Optical coherence tomography (OCT) to capture high-resolution images of the retina. Before analysis of retinal images, preprocessing is done on the image set for quality enhancement, contrast correction, noise removal, etc. These preprocessing techniques ensures that the images are optimized for accurate analysis. After preprocessing, features such as : microaneurysms, hemorrhages, exudates, and neovascularization, are extracted from the image set. Features may include morphological features, texture, vessel segmentation, etc. Extracted features are then fed into the machine learning algorithms like support vector machine, random forest classifier, or may include deep learning models. These algorithms learns the hidden patterns from the features and classify the images into 5 grades of diabetic retinopathy. The performance of the CAD system is then evaluated using different accuracy parameters like sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC-ROC). The results are then compared with the clinical diagnosis. By integrating CAD system into clinical workflow provides timely and accurate diagnoses. It increase the potential of early detection of the disease.

2.3 Existing Research work on Computer-Aided Diagnosis of Diabetic Retinopathy

[4] Qiao et al. (2020) developed a Prognosis of Microaneurysm and early Diabetic detection system that analyses the eye fundus images to diagnose early symptoms of DR. This system specifically targets the microaneurysms as they are among the first signs of DR which enables early detection.

The PMNDPR system utilizes the Deep Convolutional Neural Network (DCNN) network plan for segmenting semantic categories in fundus images. The workflow of the system involves several key stages: Preprocessing of the images was done using Curvelet Transform there is an improvement done to the dark lesions in the retinal images.Another imaging preparation technique which is employed to enhance the contrast of bright lesions as well as in doubling the range of a filter is the use of optimal band pass filtering. Candidate Lesion Detection involved a number of image-processing methods such as Gaussian filterations, matched filters, Laplacians, and methods that maximize the mutual information between the images. During the calculation of correlation coefficients of each pixel, non-linear filters with Gaussian kernel is applied. Dimensionality reduction is performed next on the data by utilizing the Principal Component Analysis (PCA) to extract relevant features. Feature Extraction and Classification done by convolutional layers. Convolution layer extracts some features of the given input, which is then flattened and passed to a fully connected layer followed by ReLU activation that creates a 336 features vector.The resultant contour is then passed through a softmax function that generates class probabilities that enhance the classification of the detected lesion.

The PMNDPR system aids in detecting both dark and bright lesions differing stations between them and exhibiting sensitivity in contrast to specificity. The estimated reported average sensitivity value for identifying dark lesions are 97% while specificity is at 99. 4%, 98. 4%, and 95. 1% whereas in case of bright lesions the sensitivity and specificity value lies at 96. 8%, 97. 1%, and 95. 3%.

The technique successfully detect lesions. This work apply efficient preprocessing techniques such as Curvelet Transform, PCA, and bandpass filtering . As a result, image quality and feature extraction improved. There are variety of lesion type available. For a model to be robust it has to be flexible to all kinds of lesion. This work has successful in this and outperformed some standard approaches like Support Vector Machines (SVM) and Gaussian Mixture Models. However, the model is highly dependent on the training image quality. Despite of over all high

accuracy the system often produces False Positive and false negatives results. Also the model is highly complex and resulting a long time for training restricting manual maintenance.

This study highlights the efficiency of Deep Learning algorithms such as DCNNs for early detection and classification of diabetic retinopathy. This effective preprocessing and flexible candidate lesion detection helps to ace high sensitivity and specificity but the model's complexity makes it harder for practical implementation.

[5] Qummar et al. (2019) identified the interest of the study in using end-to-end deep learning ensemble network for the detection of different stages of diabetic retinopathy (DR). The ensemble model used in this paper combines four effective architectures namely, ResNet50, Inception V3, Xception, and DenseNet121 to improve the performance and detection system's resilience.

The ensemble framework makes use of several deep learning models to reduce the model's overall predictive error. To handle data imbalance issues, the study first applies both upsampling and downsampling strategies to the data during the preprocessing step, which helps to make the DR stages of the training images more balanced.

The final layer involves the meta-algorithm of stacking used for aggregating the predictions of the various models to optimize performance. The categorical cross entropy loss function which works best for multi-class classification as we have here is used and the optimization is done with Nadam Nesterov accelerated gradient method. This optimizer is best well known for it sparse gradients and the speed converge while maintaining balance of optimization stability. The study also underlines the need of varying other big parameters including the learning rate since it varies from 0. 1 to 0. The specification 001 greatly enhances the performance of the model in relation to other assessment criteria's. Despite the popularity of Adam optimizer in computer vision, this study chooses SGD optimizer for DR grading and asserted that SGD offer better outcomes in terms of DR grading.

They achieved the average accuracy of 80%. The recall for class 0 (Normal) has the highest recall signature owing to many negative instances in the dataset. But the recall of class 1 (Mild) is comparatively less, due to the signs convey this stage are softer in exposures. The model also tests a high level of specificity equal to 0. The precision is also 0. 63. The F1 score, which is the conflicting coefficients of the precision and the recall, is, however, a small of 0. 53 more or less, which means the program has found some of the information but may have missed others in the trade off between precision and recall.

By ensembling different models it improved the performance of the model drastically. Adjusting the learning rates can greatly enhance the performance of the model. In this approach they utilized the stacking technique of ensemble , which combines prediction of different models and improve the accuracy and robustness of the model. But the model may fail to recognise all stages of the Diabetic retinopathy correctly. The model significantly fails to deal with the imbalance data issue. Hence the model shows low F1 Score of 0.53 indicating a considerable trade-off between precision and recall, which will impact the model performance. This study's preference for SGD over the Adam optimizer, as well as the relevance of hyperparameter adjustment, are significant contributions.

[6]In the study conducted by Momeni Pour et al., (2020), the authors employed additive colour cast correction and contrast enhancement for the preprocessing of the images in addition to the application of Efficient CNNs for the detection and monitoring of DR.

For Preprocessing CLAHE is used to enhance image quality and normalize intensities because it is effective in handling intensities through limited adaptive histogram. This particular step entails a way of optimizing input images for better enhancement before feeding them to the DR monitoring model.

When it comes to classification, EfficientNet B5 architecture is used. EfficientNet is a model that is recognized for its ability to scale the dimensions of the network structures uniformly as well as decreasing parameters and operations to increase accuracy, and maximize the limits of model efficiency. Several hyperparameters are adjusted in EfficientNet which include depth, width, and resolution scaling for enhancing the belief of the model.

The selected EffcienttNet model is trained on a pre-processed dataset created by combining the Messidor-2 and Messidor datasets. The model's performance is tested on the IDRID dataset, which also gives the clue to generalization performance of the proposed model on varied images other than those used in training the model.

The proposed method achieves significant performance metrics like sensitivity 92%, this represents the extent that the model can correctly classify the patients with positive findings of DR.

The trained model has an 92% accuracy with an AUC of 0.94. Additional findings by [7]Mohammad et al . showed that sensitivity and specificity rates of the model were 89% and 5%,

respectively, confirming that the algorithm accurately differentiates between DR and non-DR .

Optimizing the parameters proposed in this method improves the conventional models significantly; particularly, the AUC is improved by more than 0. 936 to 0. 945 on the Messidor dataset The choice of a suitable dataset is critical in establishing the initial measure of an effective classifier CBSince several datasets are available, it is crucial to choose the appropriate set of images when-measuring the effectiveness of a classifier called the measuring image: on the Messidor dataset

This approach enhanced Preprocessing with CLAHE. When the CLAHE method is applied it is possible to gain striking input images with standardized inputs, which is impossible when using such methods as HE or AHE. This work implements EfficientNet. EfficientNet B5 is catalytic in the scaling of the model as it increases the accuracy and computational efficiency by downsizing and optimizing the parameters and operations. This innovative approach achieved a good performance without Data Augmentation. In its approach, the method yields massive strides by eliminating hassles commonly associated with data augmentation, making the training process relatively easier.

The model is highly reliable on specific datasets such as Messidor-2 and IDRID. It results model may not work well other than that dataset. Flexibility may be an issue for this approach. Since the model using ensemble approach so using pretrained model may not adapt all characteristics of the training data and can show poor performance in test data. Manual hyperparameter tuning of EfficientNet model can be computationally expensive. This approach needs heavy hardware supports like need NVIDIA 1080ti GPU supports, which could be limiting its practical use.

Momeni Pour et al. (2020) describe a unique strategy to DR detection and monitoring that employs preprocessing techniques and Efficient Convolutional Neural Networks.

In the study by [8]Costa et al. (2018), the authors present a new approach into generation of retinal image synthesis through the use of adversarial learning frameworks. The proposed method involves two primary steps. The first step is to implement an Adversarial Autoencoder for Retinal Vessel Network Synthesis. This process replicates the distribution of retinal vessel structures, using the true distribution in training data to generate realistic synthesis images without the need to adjust parameters by hand. After the VN synthesis method, the approach employs a GAN to produce color retinal images. This approach minimizes divergences in the

distributions of both the vessel structures and the color images so that they are globally realistic.

To train the model, Messider-1 and DRIVE datasets have been used, which are well-renowned databases of retinal images.

For vessel segmentation, an encoder-decoder structure based on U-Net is employed for a solid base also to model veins' shapes and patterns effectively.

The subjective impression of the synthetic images, and the expressed opinion about them, as well as the quantitative measures, namely the ISC values are used for performance assessment of the synthetic images.

The study presents the following key findings: Synthetic images are more global than retinal images which tend to mimic the retinal images by their structure and other things. The mean ISC score for real images is 0.9832 with a standard deviation of 0.1117. In the case of a synthetic image, the value of ISC is 0.9671 with a standard deviation of 0. 0307. These scores show that although synthetic images are synthetically perfect and the method produces nearly perfect segmentation divisions, the vessel segmentation scores are slightly lower in comparison to the scores of real images.

Combined with adversarial learning, the model will effectively reach the distribution of retinal images from training data and perform parameter tuning. After once training the model can generate a high number of synthetic images without training repeatedly. It simplifies the data generation pipeline. In other conventional methods, different parts of retinal morphology are generated separately. However, this process generates retinal images in a unified manner.

Since the model is trained on a small dataset, 614 images of the Messidor-1 database, it may cause biases and not be flexible to all classes.

Synthetic images are generated of dimension 224 X 224 which is lower than real retinal images. This may cause a loss of features from the retinal images, which may impact the result eventually.

[9]Araújo et al. (2020) proposed a new method for data augmentation that was developed as a way to promote the detection of PDR from eye fundus images. The technique is the creation

of synthetic cases of Neovascularization (NVs) to create additional grade 4 diabetic retinopathy cases, increasing the variation of the training set.

The workflow of this approach: First Neovascularization Generation. Semi-random Generation Algorithm is used for this purpose. Artificial NVs in synthetic images are generated employing semi-random methods with certain parameter settings to resemble actual neovascularization shapes like tree-like, wheel-like, or broom-like formations. The synthetic NVs are recognized by branching patterns, orientation and growth for this the branched structures constitute a diverse range of shape.

The potential locations for the insertion of NVs are defined statistically and presented mainly in the area of the optic disc and its neighborhood. Regarding the insertion of NVs, the number of NVs inserted per image is made probabilistic in order to be realistic.

NV colors are then aligned with the surrounding vasculature using the computed color matrix that is generated from the color of the vessels. They mix the NVs into the images with regards to the type of vessel and its relative distance to the optic disk.

They also artificially insert new NVs as additional images to the original Kaggle DR detection images, especially in grade R4 images and equitably distribute the NV-inserted images from the grades R0 , R1, R2 & R3.

One way of achieving this is by subjecting the generated NVs to the evaluation of special experts ensuring they have the likeness of true neovascularizations.

The DRGraduate model is trained using the augmenting datasets with the cross-entropy loss function being a focal point. It also used the training approach that ensures the participation of all the DR grades to check the performance of the model through GDAL datasets.

By the help of classification and regression, the detection accuracy has improved up to 0.71 to 0.74. It also gives better results in terms of classification between the images that have been labelled with R4 and the rest. Further, analysis from specialists supports the notion that synthetic NVs closely resemble true neovascularizations making the dataset compelling. The augmentation process does not modify the original R0-R3 images but adds alteration to the R4 images as received.

The data augmentation drastically increases the accuracy of the model for severe cases. The synthetic NVs are similar to the real ones, making it difficult to distinguish. Through this approach, they successfully overcome the imbalanced dataset constraint and performed better results.

However, this model generates false positive cases. This approach fails to distinguish between other morphological structures other than NVs. The model may generates unusual NVs and may cause color disparity in retinal images.

Araújo et al. (2020) effectively demonstrate the potential of data augmentation in improving the detection of proliferative diabetic retinopathy.

In the study by [**?**]de la Torre et al. (2020), the authors propose an interpretable classifier for the grading of DR disease and further focus on interpretability and efficiency of the proposed model. In this approach typically utilizes Layer-wise Relevance Propagation (LRP) system. The DR classification model is integrated with the LRP model to improve the understanding of model results. It enables one to observe the breakdown of contributions made by various features and this is very important in analyzing the decision made by a model and also very helpful in modelling to tackle problems since they come along with good explanations.

The classification process is carried out with a CNN model with 391,325 parameters for 17 layers. The network architecture includes seven blocks made up of 2-layer stacks along with a classification phase where a 2 x 2 convolution takes place. These blocks help in the extractions of features and the final output scores, which is then transformed into probabilities by the SoftMax function to ensure the model is optimized in its prediction. The model uses Quadratic Weighted Kappa (QWK) as a loss function, which is adequate when targeting ordinal classification such as DR grading.

The performance of the model is as follows: In the validation set, the model produces a QWK (Quadratic weighted kappa) of 0.814 on the validation set. They again evaluated the model on the test set and with the help of this model they were able to get QWK score of 0. 801.

When performing feature averages from both eyes using a linear classifier it was possible to record an overall QWK score of 0.844.

By incorporating the mentioned LRP model, it makes the classifier decision-making process

quite interpretable. This is because the decision support is provided by using the explanation model and this improves the classification accuracy.

This approach also faces some setbacks. Finding one type of diabetic retinopathy calls for a few tests, which can consume so much time. The model can't deal with data imbalance whereby the model could be skewed by a certain type of data and thus enhances the bias of the predictions made. The training time is very high for the model and also computationally expensive.

Overall, this approach not only increases the accuracy but also increases the interpretability. Techniques like model pruning, quantization, and knowledge distillation can be used to reduce the computational requirements of ensemble models. Utilizing distributed computing frameworks to parallelize the training process can help manage computational demands. Incorporating attention mechanisms into ensemble models can improve the ability to localize specific features in medical images. Implementing multi-scale analysis techniques can enhance the model's ability to capture both global and local features.

2.4 Gaps in Current Research

The current state of research in Deep learning based techniques in diabetic retinopathy diagnosis shows several limitations. These limitations include imbalanced data handling, computational complexity, bias toward some grades, poor performance in detecting proliferative DR cases, model interpretability issues, and accuracy not meeting expectations. To overcome these difficulties, my research will look into several crucial steps like handling imbalanced data, effective preprocessing, and high accuracy in detecting proliferative DR. I will explore especially tailored preprocessing approaches for analyzing eye fundus images and give a comparative study on those approaches. To imbalance the dataset, I will use sampling strategies. This will ensure equal representation of all grades and thus improve the generalization of the model. [10]

By implementing ensemble learning approaches, I aim to combine the strengths of several pretrained deep learning models to improve overall performance. Ensemble learning has the potential to improve model generalization and reduce overfitting, resulting in more accurate diagnosis outcomes. My research uses these approaches to advance the state-of-the-art in deep learning-based DR diagnosis by addressing recognized gaps and limitations.

Chapter 3

Problem Statement

3.1 Problem Definition

To help the ophthalmologists to diagnose DR with greater precision or potentially automate the diagnosis part, we may use the computer algorithms to analyze eye images and catalogue the disease into one of five progressive levels of severity; including no disease. This form entails the aim and shoot of the eyes' fundus through polarized cameras including fundus cameras and retinal cameras. After the images are acquired, the enhancement process of the images takes place to make the images more lucid by applying some of the filters from the computer vision. Subsequent to this improvement, computerised software that comprises complex formai like deep learning models are then used to identify patterns in these eye images, not dissimilar to the capacity of human brain to detect complex designs.

Starting with label pre-processing, the deep learning model identifies a massive amount of fundus images labeled with respective diseases. During the training phase, the model settles to hidden features of DR by learning important features such as spot of blood, swelling, and abnormal vessel growth. After the model has been sufficiently trained it is intended to predict and label grades of diabetic retinopathy based on their level of severity on a scale of 1 to 5.

The main research question of this study is related to the increased correct identification of diabetic retinopathy – the most common eye disease affecting vision in persons with diabetes using deep learning techniques and an ensemble model to address the issue. Ensemble learning is, therefore, a process that works in such a way that it takes several initially trained models and tries to capitalize on the streenghts of each model and avoid his weaknesse. Screening examination of diabetic retinopathy is important to avoid severe vision loss due to diabetes

because DR is considered a major cause of vision loss and blindness in the diabetic population. It is required to employ modern and efficient automated methods for diagnosing diabetic retinopathy based on the retinal images, as the manual analysis by the ophthalmologist is a very lengthy, ineffective, subordinated to errors, and very expensive process. These restrictions imply computerized diagnostic and therapeutic calibration misses and increased urgency for development of enhanced technologic tools.

Another disadvantage or complication of implementing these automatic diagnosis systems is the variability in the images of retina, which in turn is likely to affect the efficiency of the automatically developed systems. Hence, it is essential to have strong preprocessing techniques that tackle these potential disturbances. These preprocessing methods improve image quality by methods that augment cues in DR at various stages relevant features come easily more distinguishable. Nevertheless, most conventional preprocessing techniques may not work well at giving required edge enhancements for medical images especially eye fundus images. This is due to the fact that the blood vessels of the eye are very sensitive and the symptoms of diabetic retinopathy may easily be concealed and hence care has to be taken in the choice of the kind of image preprocessing methods to be used on eye fundus images.

In this paper, different preprocessing techniques are evaluated in order to determine their effects on the effectiveness of the ensemble models regarding DR detection. In the subsequent analysis, an ablation study on various preprocessing techniques will be carried out, including but not limited to Contrast Limited Adaptive Histogram Equalization and Ben Graham's preprocessing together with a new proposed method that combines CLAHE and preprocessing by Ben Graham. Therefore, the question which may be answered is to identify which of the approaches can assist in the enhancement of the accuracy of each grade DR. With this approach that we are outlining in this paper, we hope to determine which of the preprocessing methods is most beneficial for the detection of certain levels of DR. Based on this background, the following hypotheses are formulated to guide the study: The application of the preprocessing techniques will improve the discriminative properties of the models by increasing image contrast and decreasing noise, which in turn will improve DR sign detection. This is a technique similar to the standard image enhancement technique that corrects on the contrast of images without increasing the noise significantly and hence leading to over-enhancement. One of the techniques deployed to preprocess the images is the one developed by Ben Graham from Kaggle competition where contestants were requested to diagnose diabetic retinopathy in 2015; which involves resizing the images to uniform size, applying Gaussian filter to smoothen the images and normalizing the pixel intensities. Taking inspiration from CLAHE and Ben Graham's approach, in this project tried to build a novel approach for detecting proliferative DR images.

The aim here is to create a system that not only yields high diagnostic accuracy but also needs minimal rearrangement of the clinical day. This integration must be pursued to optimise screening efficiency and facilitate early identification of patients at risk of severe visual deterioration. As this study seeks to evaluate the various levels of the DR and quantify the efficiency of the preprocessing techniques as strategies for detection of different levels, it will go a long way in enhancing clinical accomplishment and subsequently, improving patient leading a better, healthier life.

In terms of practical implications, it is possible that incorporating such complicated preprocessing procedures, as well as the aforementioned learning frameworks, into clinical practice may significantly revolutionise diabetic retinopathy diagnostic and management approaches in the future. For example, in situations, where trained personnel such as ophthalmologists are scarce, as is thecase in many developing nations, such automated systems may act as an imperative early diagnosis platform. Furthermore, since patient's files in the clinic system are accessed by other staff members it can help to reduce the burden on the ophthalmologist as well as decrease the likelihood of erroneous diagnosis which can occur when diagnosis is made from ementary data from patients' files.

However, employing a method that can differentiate the outcome of this complication into various grades is much more precise and can help fine-tune the approach to the patient's condition. Those who have the early stages of DR can benefit from the interventions being put in place to prevent further escalation of the condition while on the other end, those with advanced stages can undergo closer monitoring and early treatment to reduce their likelihood of blindness. It was established that it is possible to promote improvement in patient care through the application of these technologies.

This study also investigates the broader implications of deploying such high-throughput deep learning models in clinical settings. Therefore, this study intends to find out the imperative gaps that has been addressed in the current research work in terms of proposing enhanced preprocessing methodology for preprocessing eye fundus images particularly for the diagnosis of diabetic retinopathy and further using ensemble learning models for improving the diagnosis accuracy and reliability of the system. By critical assessment of numerous instances and selection of relevant examples for preprocessing, the goal is to determine the optimal strategies for detecting DR grades. The primary goal of this research is to develop a highly accurate, efficient, and clinically integrated system that shows a high accuracy in classifying Proliferative Diabetic Retinopathy (DR), despite the limited availability of proliferative DR images. This includes providing a comparative analysis of various advanced preprocessing techniques and hopes to create

a valuable resource for the future researchers.

3.2 Research Question

The research indeed poses two fundamental questions that are germane to the proposition of moving forward in the diagnosis of DR using deep learning. The first question is asking which preprocessing method - Contrast Limited Adaptive Histogram Equalization (CLAHE), Ben Graham's preprocessing or both methods- will perform better in the detection of different grades of DR. Hence, hence fundamental techniques known as preprocessing techniques used in the enhancement of retinal fundus images are of outmost importance in determining the severity of the disease by affecting the deep learning model's ability to recognize and classify the diseases. This research aims to conduct an ablation study to compare the effectiveness of these techniques across different grades of DR: It includes No Diabetic Retinopathy (DR) G 0, Mild DR G 1, Moderate DR G 2, Severe DR G 3 and Proliferative DR G 4. The hypothesis that can be formulated is that after applying the given preprocessing methods, the diagnostic results will improve for each of the grades and possibly some of them are more efficient for particular stages of DR. This work aims at comparing the effectiveness of the various preprocessing techniques in a bid to recommend the best approaches that can help enhance the detection of DR to an extent that the quality of the patient's lives is improved.

The second research question is how to increase the efficiency of an ensemble model, using existing deep learning architectures like InceptionV3, ResNet50, EfficientNetB5, and DenseNet169. Ensemble learning is the process of training more than one model and then aggregating them in the hope that the attributes of each model would complement each other, pointing to a better improvement or reduction of the weaknesses that each of the models portrays. All of these models have been able to prove different level of proficiency in image classification exercises, but their normalized performance may differ based on the characteristics of the data set and the kind of preprocessing involved. This study will compare the performances of these models separately and combined as well as examine and enhance the classification of all DR grades including Proliferative DR, which are particularly difficult to detect. The procedure of the study will be in assessment of the stacking ensemble strategy in increasing diagnostic performance and reducing slanting.

It will also analyze how the use of advanced preprocessing techniques affects the performance of these models. It will also investigate how improved preprocessing techniques influence the

performance of these models. This study aims to develop a robust and efficient DR detection system that can be seamlessly integrated into clinical workflows, allowing for timely intervention and treatment of patients at risk of severe vision loss.

3.3 Hypothesis

This report summarises how different preprocessing strategies affect the Ensemble model's ability to identify diabetic retinopathy in the EyePACS dataset. The hypotheses are as follows: The first hypothesis is given as follows: It is believed that utilising the CLAHE method in the preprocessing stage will increase the ability to better detect Mild DR (Diabetic Retinopathy, Grade 1) and Moderate DR (Diabetic Retinopathy, Grade 2). It is believed that CLAHE will enhance image contrast and help make early grades of DR more visibly distinguishable by clearly revealing the small pathological features perhaps making their identification quicker and more accurate.

The second hypothesis posits that another kind of preprocessing technique referred to as Ben Graham's method will prove more useful in identifying Proliferative DR (Grade 4). Where there is Proliferative DR there is extensive damage to retinal tissue and changes to blood vessels; these indicators which are difficult to identify using traditional methods may be easier to detect when using the feature extraction of Ben Graham's preprocessing technique for this method of DR.

The third hypothesis says that adoption of an improved preprocessing approach, based on both CLAHE and Ben Graham's strategy, will favorably influences the final detection performance of the system for all DR gradations. The modified approach looks forward to combining advantages of these preprocessing techniques in improving as much as possible the image quality and enhancing the conspicuity of the image features while increasing the detection rate and scope with regards to DR severity grades as much as possible.

Furthermore, the research assumes that the DR detection will be both accurate and efficient if ensembling several DL models, such as pre-established versions including Inception V3 refined neural network Resnet 50 Efficient Net b5 Densenet169. By means of aggregating various models by using ensemble learning methods, the study expects to improve the performance of the DR Diagnostic system in terms of accuracy and time efficiency as compared to other models.

These hypotheses shall serve as the foundation of the research study and shall be used in the formulation of the experimental setup, data analysis, as well as the assessment of the results of the study in an attempt to compare the effectiveness of various approaches to processing and ensemble modeling for the identification of DR.

Chapter 4

Methodology

4.1 Dataset description

The EyePACS dataset is quite valuable for analyzing DR and assessing the competence of AI schemes for diagnosing DR at an early stage. It has millions of images, especially high-quality images, and it has many eyes' images more than 35,000 images with variable sizes. this dataset has a wide difference this meaning that it has variations in imaging making it possible to carry out different Imaging, Light Variation, and Anatomical differences that exist within patients just as typical clinical settings would portray. Every picture is reviewed and diagnosed qualitatively using 5 levels of severity with senior ophthalmologists who determine the amount of Diabetic Retinopathy present in the image. They include annotations that allow for supervised learning as an aid to the clinical decision-making process given that ML models can then be trained to predict DR severity. Five classes of DR present as follows :Five classes of DR present as follows :

: No DR : Mild nonproliferative DR : Moderate nonproliferative DR : Severe nonproliferative DR : Proliferative DR

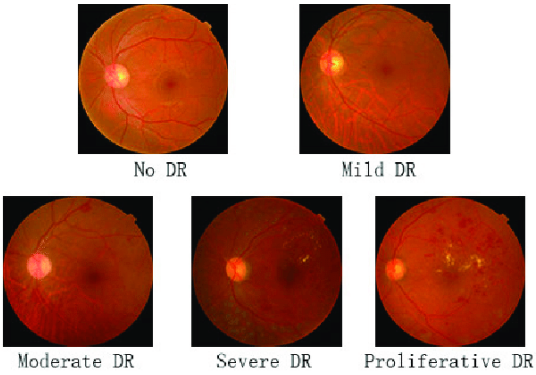

Figure 4.1: Morphology of Diabetic Retinopathy eye

A review of the EyePACS dataset shows high accuracy and efficiency of the DR screening when conducted through quantitative research. Deep learning models on this dataset yield promising high accuracy rates and the values cited were up to 99.50% and sensitivity 99.20% and specificity 100%.

However, a significant limitation faced by this dataset is, that it is highly imbalanced. Missing a couple of grades or having them assigned unevenly across the DRs is prevalent in eyepacs dataset. This distribution shows that most of the images are from patients that are mostly have mild DR. This skews the models in that while they perform very well for the majority class, they are unable to effectively classify the minority classes. Thus, models trained with imbalanced data in DR classification, that is, where little data presents severe forms of DR like Proliferative DR, will show low accuracy in their detection with negative implications on DR treatment. this problem of dataset imbalance deserves particular attention as the measures taken to tackle it are vital for improving the stability and interpretability of estimates in DR detection models.

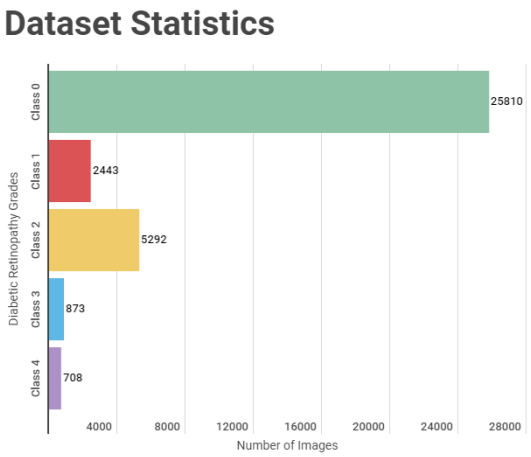

Figure 4.2: Distribution of Eyepacs dataset

The EyePACS dataset is an important component of DR research since it provides a diversified and annotated collection of retinal fundus images that can be used to train high-performing detection algorithms.

4.2 Analysis of Design Requirements

This part discusses the intricacies involved in creating an efficient system, for conducting a study on preprocessing methods to detect diabetic retinopathy (DR) using an Ensemble model. The goal of the project is to build an automatic system that efficient in classification of different grades of DR. An ablation study is done on some special preprocessing techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) and Ben Grahams approach and a modified one. This initiative hopes to meet the demands of ophthalmologists who need precise diagnostic instruments to enhance patient results.

4.2.1 Analysis of Dataflow

The data flow analysis outlines the interaction of data with the different components of the system designed for detecting diabetic retinopathy (DR) using an ensemble model. The goal is to improve detection accuracy and efficiency by experimenting with various preprocessing techniques and using an ideal emsemble model.

4.2.2 Overview of Data Flow

Overview of Data Flow. The data flow in the system can be divided into five stages: data collecting, preprocessing, model inference, ensemble prediction, and evaluation. Each stage is critical to guaranteeing the system's efficiency and accuracy.

Data acquisition: The first phase involves collecting data from the Kaggle Eyepacs dataset. Eyepac dataset is alarge dataset with thousands of high resolution eye fundus images. This images varying in size and quality. Each eye images meticulously labeled with a severity level of DR, ranging from 0 (No DR) to 4 (Proliferative DR). The data distribution is not balanced for each grade. Hence dataset balancing is a must needed task while dealing with the eyepacs dataset.

Data pre-processing: The raw pictures are improved in quality during the preprocessing stage in order to prepare them for model training. Two essential preprocessing approaches are used:
(i)CLAHE (Contrast Limited Adaptive Histogram Equalisation): Increases picture contrast, making fine details like microaneurysms and haemorrhages more visible.
(ii)Ben Graham Preprocessing: This process focuses on decreasing noise and preserving structural details, which improves the visibility of proliferative DR characteristics.
(iii)Modified approach: By taking inspiration from both CLAHE and Ben Graham's process, a modified technique is applied on images and evaluated its results. These preprocessing approaches are vital for increasing picture contrast while reducing noise, hence revealing critical pathological characteristics associated with various DR phases.

Training: The preprocessed images are then fed into the base deep learning models of the ensemble system, which are already trained. This ensemble model consists of InceptionV3, ResNet50, EfficientNetB5, and DenseNet169. Each model is fine-tuned using preprocessed photos to understand the patterns and characteristics associated with the various DR phases. Ensemble Model Training:
InceptionV3 uses its deep architecture to capture complicated patterns in retinal pictures.
ResNet50: Uses residual connections to solve the vanishing gradient problem, resulting in robust learning.
EfficientNetB5 optimizes depth, breadth, and resolution to obtain great performance with fewer parameters.
DenseNet169 connects each layer to every other layer, allowing for more efficient feature reuse.

Ablation Study: An ablation study is conducted to evaluate the effects of various preprocessing techniques. By applying one preprocessing approach at a time and analyses the resulting model performance. The study explores how each technique contributes to the model's overall accuracy and resilience.

Evaluation: After completing the training of the ensemble model, the ensemble model's performance is evaluated using a variety of measures, including accuracy, precision, recall, F1 score, and ROC curve.

Output and Inference: After finishing model training and evaluation, the ensemble model is applied to a new collection of retinal pictures for categorization. The model predicts the severity of DR for each image, enabling a thorough evaluation of the new data. The categorization findings are kept for future examination and clinical decision-making.

Process:
Input: Preprocessed retinal images.
Model: Ensemble of InceptionV3, ResNet50, EfficientNetB5, and DenseNet169.
Output: Predicted severity level of DR for each image.

Final output: The categorization results indicate the severity level of DR for each picture. These findings are critical for determining the efficacy of preprocessing strategies as well as the overall performance of the ensemble model. The findings are especially important in clinical settings, assisting in the early diagnosis and quick management of diabetic retinopathy.

DFD-0

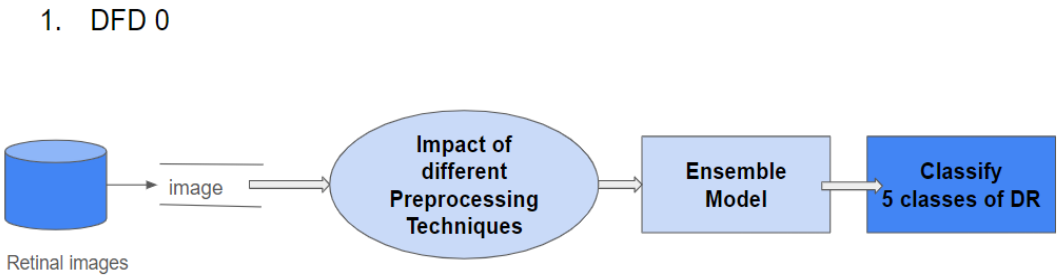

Figure 4.3: DFD-0

DFD-1

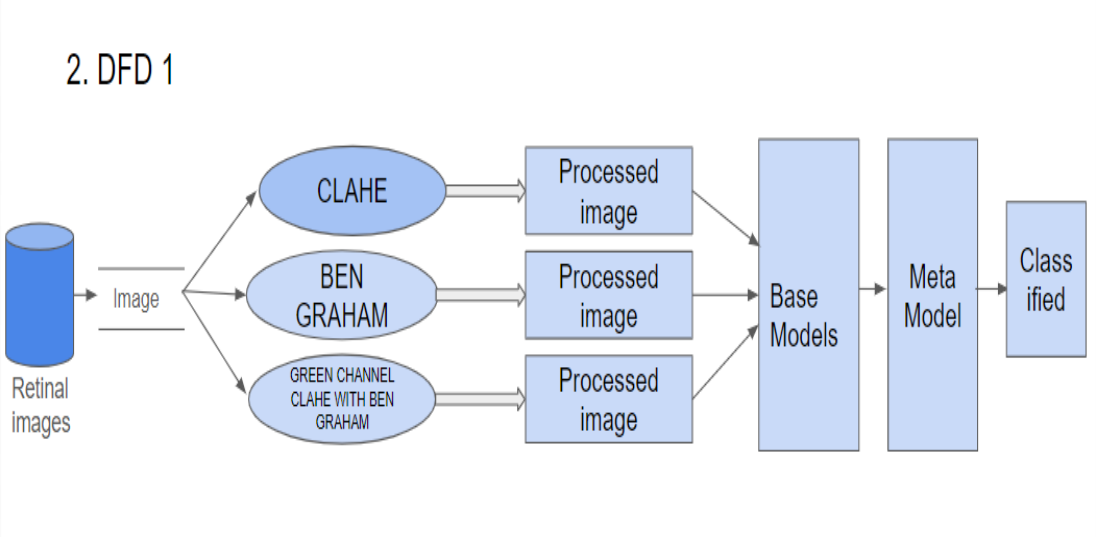

Figure 4.4: DFD-1

DFD-2

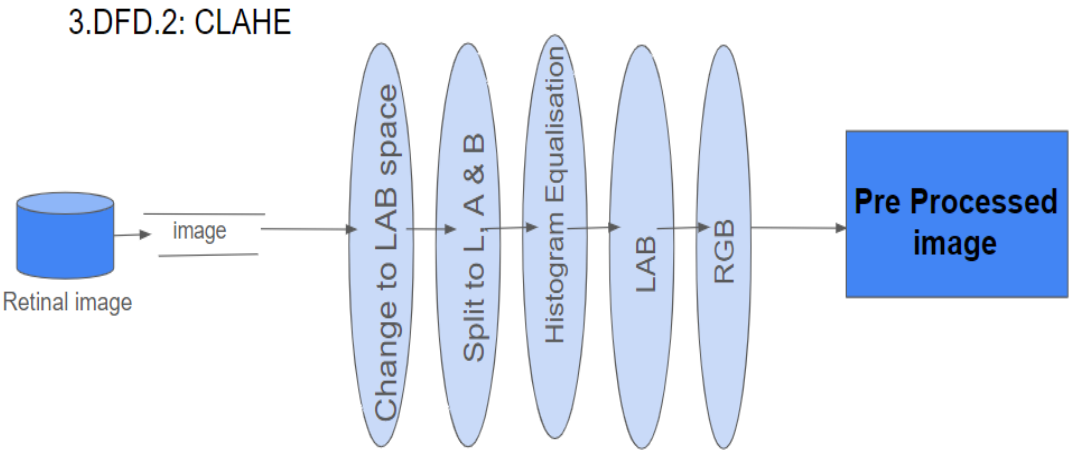

Figure 4.5: DFD-2

DFD-3

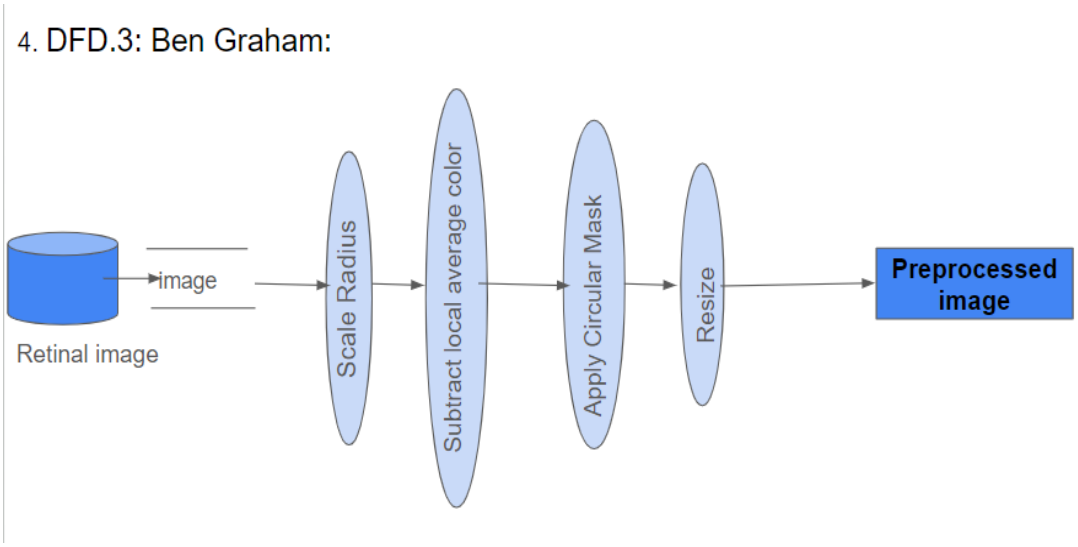

Figure 4.6: DFD-3

DFD-4

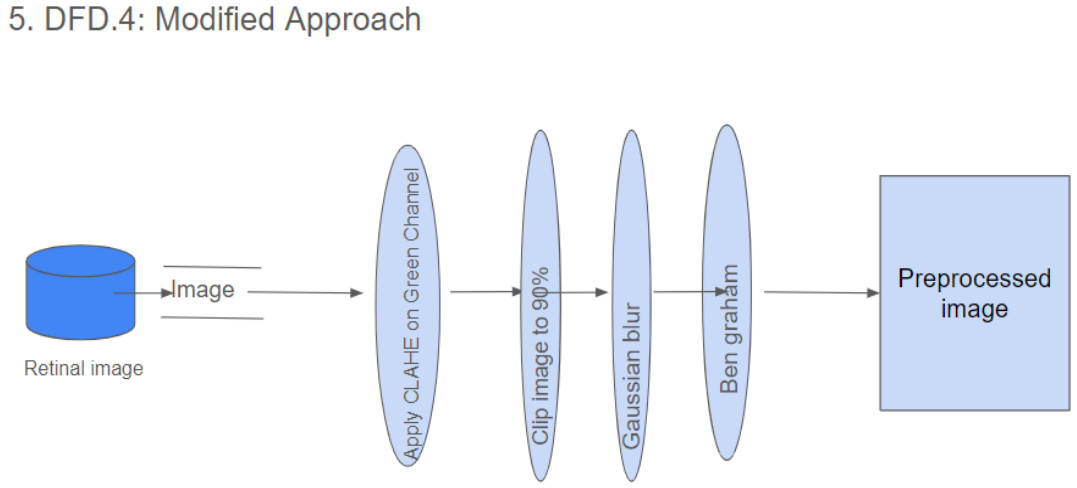

Figure 4.7: DFD-4

4.3 Hardware-Software Architecture

A thorough hardware and software setup was required for the development and deployment of the Ensemble Learning Model for diabetic retinopathy diagnosis. This ensured efficient model training and testing. The hardware used contained both local system resources and cloud-based

infrastructure, each of which had distinct benefits.

Hardware setup:

Local system:

RAM: 8GB purpose: This will ensure faster data preprocessing and training of the model. GPU: NVIDIA GeForce GTX 1650 Purpose: It is required for handling the complexities during the training of ensemble model

Cloud Platform:

Platform: Google Colab Pro+. Purpose: To run scalable computational resource for the training of the model.

Using a local machine with a dedicated GPU made it easier and more efficient to create and test code locally. However, for more resource-intensive operations, like as building big models on massive datasets, cloud-based GPU instances like Google Colab Pro+ provide substantially greater computational power and memory capacity, allowing for quicker experimentation and model training.

Software setup:

Operating system: Type: Microsoft Windows 10 Purpose: Compatibility with deep learning frameworks and development tools. Python Version : 3.12.2 Purpose: Programing language used for development of the system. Deep Learning Framework: TensorFlow and keras purpose: The Ensemble Learning Model for detecting diabetic retinopathy will be implemented and trained using TensorFlow and Keras. TensorFlow and Keras are strong tools for creating and training deep learning models, with substantial documentation and community support. Key libraries:

TensorFlow : It is a core deep learning library for creating and training neural networks. NumPy: Required for numerical computations and array manipulation. Pandas: A tool for data manipulation and analysis. Keras is a high-level neural network API built on top of TensorFlow that simplifies model development and experimentation. OpenCV-Python:Applied for image pre-processing tasks, including the application of Contrast Limited Adaptive Histogram Equalization (CLAHE) and the Ben Graham preprocessing technique, enhancing the quality of retinal images

for subsequent analysis. Optuna: Used to tune hyperparameters and improve model performance. Matplotlib, Seaborn, and Scikit-learn are data visualization and machine learning tools for analysis and assessment.

These software components serve as the development environment's basis, offering necessary tools and libraries for creating, training, and assessing machine learning models for diabetic retinopathy diagnosis. Python is the major programming language, with specialised libraries and frameworks like TensorFlow, PyTorch, Pandas, scikit-learn, Matplotlib, OpenCV, and NumPy providing project-specific functionality.

S/W architecture

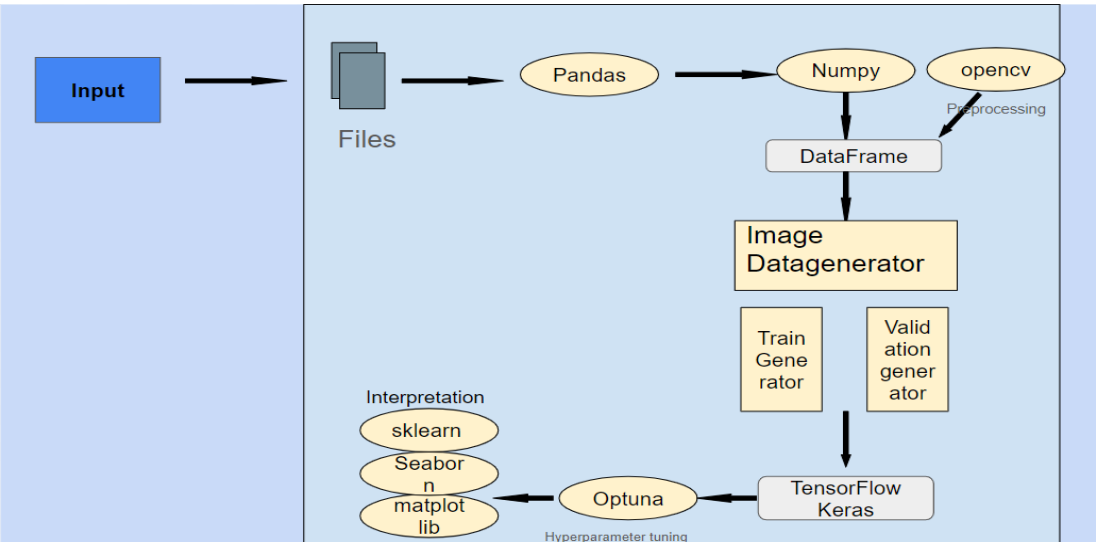

Figure 4.8: Software architecture

The Development Environment:

VS Code: It is an integrated development environment (IDE) that allows for efficient software development, including creating, debugging, and experimenting with code. Developing Environmental Identification:

Python Version: 3.12.2 The precise Python version is used for development, guaranteeing compatibility with the selected libraries and frameworks.

The Virtual Environment: Purpose: Venv was used to create and administer this project, which allowed for the separation of project dependencies and ensured consistency across multiple de-

velopment environments. Package Management: PIP: The Python package manager's purpose is to install, upgrade, and manage project dependencies, making it easier to install essential libraries and frameworks within the virtual environment.

4.4 Preprocessing Techniques applied in this project work:

Preprocessing is a crucial step in the automated interpretation of medical pictures, notably for detecting diabetic retinopathy (DR) in retinal fundus images. Preprocessing is required to increase picture quality, feature visibility, and noise reduction, hence assisting in the correct identification and categorization of illness severity. However, traditional preprocessing approaches frequently fail to match the specific requirements of medical imaging, resulting in morphological structure distortion.

Standard preprocessing approaches, like basic histogram equalisation or noise reduction algorithms, are usually focused for general-purpose picture enhancement. These approaches fails to account for the unique morphological details of medical pictures, particularly retinal fundus images. Blood vessels, the optic disc, and the macula are among the extremely sensitive and complicated morphological components seen in eye fundus pictures. Inappropriate preprocessing might distort these sensitive traits, causing morphological anomalies that make correct diagnosis impossible. For example, excessively strong noise reduction may distort crucial features, whereas inappropriate contrast enhancement may accentuate or mask vital signals of DR.

To overcome these issues, experts come up with specialised preprocessing methods for eye fundus images, such as Contrast Limited Adaptive Histogram Equalisation (CLAHE) and Ben Graham's preprocessing. CLAHE increases medical picture contrast by reducing noise amplification, resulting in increased local contrast without oversaturation. This approach is very useful for detecting minor pathological abnormalities in retinal pictures, such as microaneurysms and haemorrhages, which are signs of early DR (Grade 1 and 2). CLAHE contributes to the morphological integrity of retinal structures by retaining local image detail.

Ben Graham's preprocessing method, on the other hand, involves shrinking and centering the retinal pictures, followed by local colour normalisation. This method helps to standardise the look of the photos, making them more consistent and easier for machine learning models to handle. This approach is especially helpful for advanced stages of DR, such as Proliferative

DR (Grade 4), which has more dramatic morphological alterations. By lowering inter-image variability, Ben Graham's strategy improves the model's capacity to detect severe problems.

In this research, a modified preprocessing methodology inspired by both CLAHE and Ben Graham's methodologies is analyzed. This hybrid strategy seeks- the contrast enhancement strategy from CLAHE and centering the image and edge enhancement strategy from Ben Graham's, in order to deliver complete picture improvement. This dual technique highlights minor traits while maintaining consistency throughout the dataset, boosting the overall resilience and accuracy of the automated identification system.

These specialized preprocessing techniques like CLAHE and Ben Graham's method are essential for enhancing the accuracy of the resulting classification process.

4.4.1 CLAHE Preprocessing

Contrast Limited Adaptive Histogram Equalisation (CLAHE) is an effective preprocessing technique used extensively in medical imaging to improve image contrast. It is especially useful in retinal image analysis for diagnosing diabetic retinopathy (DR) since it highlights the subtle diseased signs required for a correct diagnosis.

Change to LAB Colour Space:
The first step in the CLAHE preprocessing pipeline is to transform the picture from RGB to LAB colorspace. The LAB color space divides the image into three components:
L(lightness): Image Luminance
A(Green-Red): Color spectrum from Green to Red
B(Blue-yellow): Color spectrum from Blue to Yellow

This splitting allows to apply Histogram equalization only to the Lightness channel without distort color distribution. This L channel is the primary target of contrast augmentation. The A and B channels, which provide colour information, stay intact during this process.

CLAHE is used on the L channel to provide histogram equalisation with a clip limit. The clip limit is a threshold that limits contrast enhancement and hence prevents noise amplification. In CLAHE these stages are involved:
(i) Histogram Equalization: This adjusts the contrast of an image by using its histogram of

frequency.
(ii) Clipping: Controls the enhancement of contrast to avoid over-enhancement, which might cause noise. This threshold is controlled by the clip limit setting. CLAHE enhances the visibility of essential characteristics such as microaneurysms, haemorrhages, and neovascularization, which are suggestive of diabetic retinopathy at various stages.

After CLAHE is applied to the L channel, the modified L channel is merged with the unaltered A and B channels to generate the improved LAB picture. The LAB picture is then transformed into RGB color space. This conversion guarantees that the image preserves its native color while improving contrast.

CLAHE impact on data types:
CLAHE requires data type modifications during processing. Images are often handled in 16-bit unsigned integer format (16u), although they are sometimes transformed to 32-bit floating-point format during CLAHE processing. This translation enables more accurate computations and modifications during histogram equalisation, resulting in higher-quality output.

Application in the detection of diabetic retinopathy CLAHE preprocessing dramatically improves retinal picture quality for detecting diabetic retinopathy.

Highlighting Pathological characteristics: Makes important characteristics such as microaneurysms, haemorrhages, and exudates more visible. Improving Diagnostic Accuracy: Clearer pictures can lead to more accurate diagnoses from doctors and automated systems. CLAHE reduces the noise impact by clipping the histogram, which would otherwise hide essential diagnostic signals.

The impact on model performance
CLAHE preprocessing has a significant influence on the performance of machine learning models used for drug detection. Enhanced contrast increases the model's ability to:
(i) Identify Subtle Features: Better recognize and classify different phases of DR.
(i) Generalising Across Variations: Perform effectively under a range of picture situations, including illumination and resolution.

CLAHE is effective in the detection of mild diabetic retinopathy
Microaneurysms, which are tiny bulges in blood vessels in the retina, are a defining feature of mild DR. These characteristics are frequently quite faint and difficult to discern without adequate picture enhancement.

CLAHE improves edge detection by helping to distinguish the borders of microaneurysms and other tiny lesions, which facilitates identification and classification by automated algorithms as well as by clinicians.
CLAHE helps to reduce background noise by minimising fluctuations in background lighting and color, which can hide the minor signals of moderate DR. CLAHE results shows more clearer picture which helps doctors to distinguish different morphology of the eye fundus.

overall, CLAHE is an effective preprocessing technique that improves the diagnosis quality of diabetic Retinopathy.

4.4.2 Ben Graham's Preprocessing:

In 2015, Ben Graham use a unique method to picture preprocessing, which helped him win the Kaggle competition for diabetic retinopathy identification. His technique employed OpenCV for preprocessing, aimed to standardise and improve the quality of retinal pictures, resulting in more resilient and accurate machine learning models.

Graham's preprocessing technique comprised three major steps:

(i) Images were rescaled to the same radius (either 300 or 500 pixels). This step assured that all photos, regardless of initial size, had the same scale. By normalising the size, the pre-processing minimised differences caused by varying camera resolutions and picture dimensions, allowing for more consistent feature extraction.

(ii) To remove the local average colour, the photos were converted to 50% grey. This approach normalised the lighting conditions over many photographs. This technique reduced the distortion caused by fluctuating light condition, which might normally hide crucial diabetic retinopathy findings.

(iii) To reduce outer boundary effects, photos were trimmed to 90% of original size. This stage was critical for removing artifacts and non-informative edges that might impede the model's capacity to learn key features. Preprocessing enhanced the signal-to-noise ratio by focusing on the image's core, the most informative area.

Graham's preprocessing method considerably improves and standardises the findings in various ways.

Preprocessing maintains homogeneity by scaling pictures to a predetermined radius. This constancy allows convolutional neural networks (CNNs) to train more successfully since the spatial correlations in the pictures stay consistent across the dataset. Mapping the local average colour to 50% grey reduces the impact of changing lighting conditions, hence normalise the lightning. This phase is critical for identifying the real characteristics of retinal pictures, such as microaneurysms and haemorrhages, which indicate distinct stages of diabetic retinopathy. Boundary Effects are reduced by cropping the photos to 90% of their original size, which eliminates unhelpful borders and concentrates attention on the centre area, which contains the majority of the diagnostic data. This concentration lowers noise and extraneous minutiae, making the important qualities stand out. Preprocessing photos improves their quality, allowing machine learning models to extract essential characteristics more effectively. This improvement improves classification performance by allowing the model to more precisely detect and discriminate between different stages of diabetic retinopathy.

Finally, Ben Graham's preprocessing technique efficiently handles the issues of unpredictability in medical imaging, particularly retinal pictures.

4.4.3 Modified Preprocessing

A new preprocessing method, influenced by both CLAHE and Ben Graham's approaches, has been analysed to improve DR identification, notably for Grades 2 and 3. This method combines the capabilities of both techniques—contrast enhancement and edge detection—to develop a powerful preprocessing pipeline for medical imaging.

Focus on the Green Channel:

The green channel of an image is crucial in medical imaging, particularly for retinal pictures, since it frequently gives the best contrast and clarity of interior structures. This channel is particularly sensitive to differences in the morphology of retinal tissues, making it excellent for emphasising diseased characteristics.
This modified approach splits the green channel and applies CLAHE to it. It enhances the contrast of the green channel which amplifies characteristics like microaneurysms, haemorrhages,

and exudates more visible. This fix uneven lighting and increasing visibility of key elements. This step is critical because it normalises the contrast across pictures, allowing learning algorithms to reliably identify and categorise DR phases.

Edge Enhancement using Ben Graham's Kernel

Following the contrast enhancement, the methodology includes an edge enhancement phase modelled after Ben Graham's method. Ben Graham's preprocessing, which won the Kaggle competition in DR detection in 2015, emphasised the significance of edge detection in reducing unpredictability caused by lighting conditions and camera settings. An edge enhancement kernel is used to enhance the edges of the feature.

To further enhance the pictures, the preprocessing pipeline includes a clipping phase that removes border effects by masking the image to keep just the core region, which is usually the most diagnostically significant component. This is followed by Gaussian blurring, which smoothens the image, reduces noise, and highlights the improved features from the previous phases.

These preprocessing techniques together considerably increase the model's ability to identify and classify DR. The preprocessing pipeline enhances the contrast of the green channel, making small DR signals more noticeable. The edge enhancement stage emphasizes these characteristics, making them more identifiable to both human observers and automated systems.

The modified preprocessing technique, inspired by CLAHE and Ben Graham's methodologies, provides a comprehensive enhancement of retinal images.

4.5 Algorithm Proposed for Preprocessing

In this part, we show the best preprocessing methods designed specifically for diabetic retinopathy (DR) detection with ensemble learning models. The proposed approach incorporates sophisticated preprocessing techniques to improve the accuracy and reliability of ensemble model classification. The preprocessing pipeline seeks to increase DR detection systems' diagnostic performance by carefully optimising picture quality and feature extraction.

4.5.1 Implication of CLAHE

A function is designed to perform CLAHE on a single-channel grayscale picture, which is commonly obtained from a colour retinal image. procedures involved are listed below:

Convert to gray scale image: The RGB input image is convertaed to the gray scale image by using cv2ċvtColor() method and the cv2ĊOLOR_RGB2GRAY option. This step makes sure CLAHE only works with single-channel pictures.

Convert to 8-bit Unsigned Integer: Then grayscale images are converted to an 8-bit unsigned integer format using the cv2ċonvertScaleAbs() method. This conversion guarantees that the pixel values fall within the acceptable range (0 to 255) for subsequent processing.

Then CLAHE object is created using cv2.createCLAHE() method. CLAHE shift pixel intensities in a small neighbourhood and redistributes it. This enhance the visibility of dark and bright features. Parameters ClipLimit and tileGridSize determines the level of contrast enhancement and the size of the local areas, respectively.

Convert to Float32: CLAHE's output is initially an 8-bit unsigned integer format. To enable further processing and retain precision, the picture is transformed to a 16-bit unsigned integer array using np.array() and the proper data type. The astype() function is then used to convert it to float32, ensuring compatibility with the other float32 pictures in the pipeline.

Finally, the image is converted back to RGB format using the cv2ċvtColor() function with the cv2.COLOR_GRAY2RGB flag.

These processes implements CLAHE on the image to enhance the contrast of a single-channel grayscale image

Mathematical formulation of CLAHE processing

Preprocessing Steps:	Mathematical formulation
1. Convert RGB to Grayscale	$I_{\text{gray}}(x,y) = 0.299R(x,y) + 0.587G(x,y) + 0.114B(x,y)$
2. Convert grayscale to 8-bit unsigned integer	$I_{\text{gray\_8u}}(x,y) = \text{round}(I_{\text{gray}}(x,y))$
3. Create CLAHE object clahe with clip limit 2.0 and tile grid size (8, 8)	The CLAHE transformation $T(i)$ is given by: $T(i) = \frac{\text{clip}(h(i))}{\sum_j h(j)} \times (L-1)$
4. Apply CLAHE to 8-bit	$I_{\text{gray\_8u}}(x,y) = \text{round}(I_{\text{gray}}(x,y))$
5. Convert to 16 bit	$I_{\text{CLAHE\_16u}}(x,y) = \text{uint16}(I_{\text{CLAHE}}(x,y))$
6. Convert 16 bit to float 32	$I_{\text{CLAHE\_float32}}(x,y) = \text{float32}(I_{\text{CLAHE\_16u}}(x,y))$
7. Convert float 32 to RGB and resize	$I_{\text{RGB}}(x,y) = [I_{\text{CLAHE\_float32}}(x,y), I_{\text{CLAHE\_float32}}(x,y), I_{\text{CLAHE\_float32}}(x,y)]$

Figure 4.9: CLAHE processing

CLAHE Images

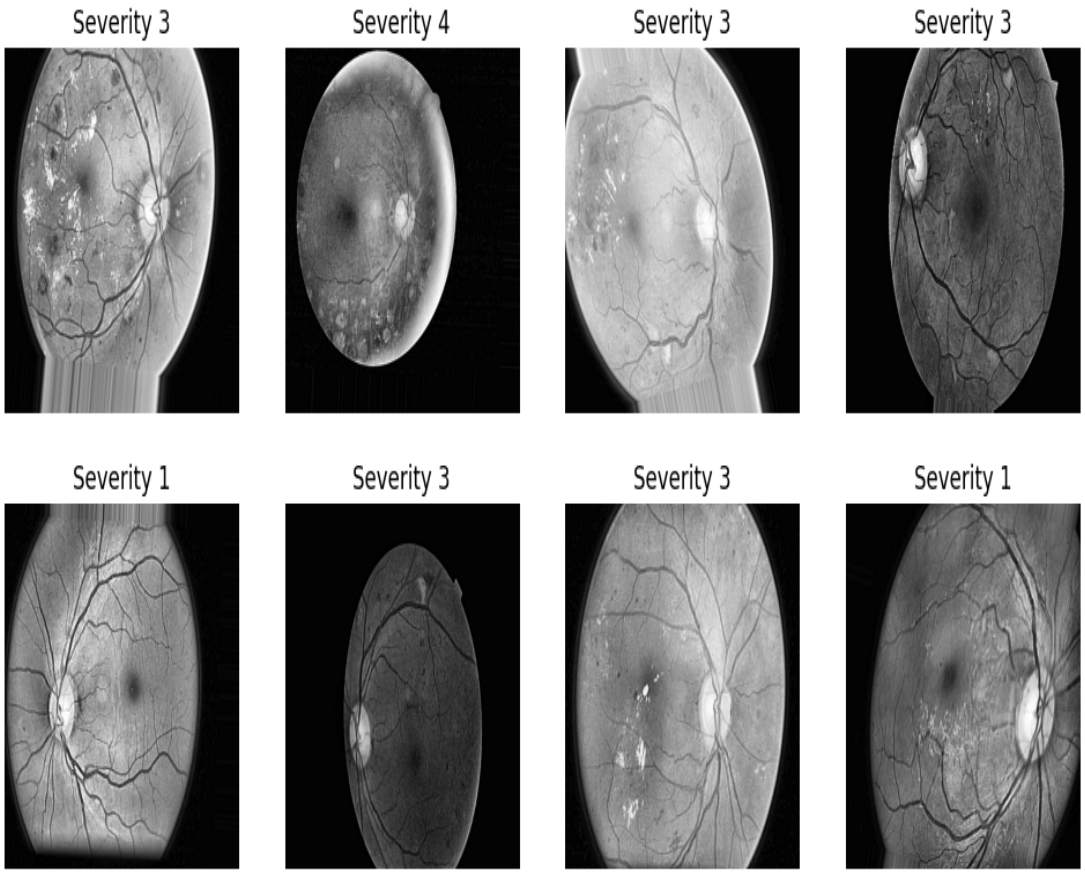

Figure 4.10: CLAHE Images

4.5.2 Implication of Ben Graham's Preprocessing

The primary concept Ben Graham's preprocessing follows edge enhancement and standardization of the image.

A function scale_radius() is created. This function scale the image to a certain radius. It computes the radius by summing the pixel intensities along the horizontal axis of the image's middle row and using the mean intensity. The image is adjusted to obtain the necessary radius by modifying the scaling factor, ensuring that the size is consistent among photos. This process standardizes the image.

The function subtract_local_average_color() is created to subtract the local average color to smooth the pixel intensities. First it uses a Gaussian blur on the input image, this removes the noise. After that, a weighted subtraction is used to remove the local average color from each pixel in the picture. The weight apply is a factor of four. This amplifying the difference between the original pixel value and the pixel value after applying Gaussian blur.

A final function clip_image() is used for reducing the image to 90% of the original size. This removes the boundary effects and standardizes the pixel size. The image is initially scaled to a radius of 300 pixels with the scale_radius function, then subtract the local average color, after that steps clipping is done on the image. This is done by creating a circular mask to keep the middle part of the picture while removing the outlying 10%. After this image is resized to its original size, here it is (224,224). It guarantees that the input dimensions remain consistent for further processing stages.

Mathematical formulation of Ben Graham's processing

Preprocessing steps:	Mathematical formulation
1. Compute the sum of the pixel values among the width at the vertical center.	$x(j) = \sum_{k=0}^{C-1} \text{img}\left(\left\lfloor \frac{H}{2} \right\rfloor, j, k\right)$
2. Compute the radius	$r = \frac{\sum(x > \frac{\text{mean}(x)}{10})}{2}$
3. Compute the scaling factor	$s = \frac{\text{scale}}{r}$
4. Resize the image	resize(img, scaleX1/r)
5. Apply Gaussian blur	GaussianBlur(img,(0,0),10)
6. Add weights and subtract the local average	$\text{result} = 4 \cdot \text{img} - 4 \cdot \text{blurred\_img} + 128$
7. Clip the image	$\text{mask}[x, y] = \begin{cases} 255 & \text{if } (x - \text{center}_x)^2 + (y - \text{center}_y)^2 \leq 270^2 \\ 0 & \text{otherwise} \end{cases}$
8. Resize the image	cv2.resize(clip_img, target_size)

Figure 4.11: Ben Graham's processing

Ben Graham's image

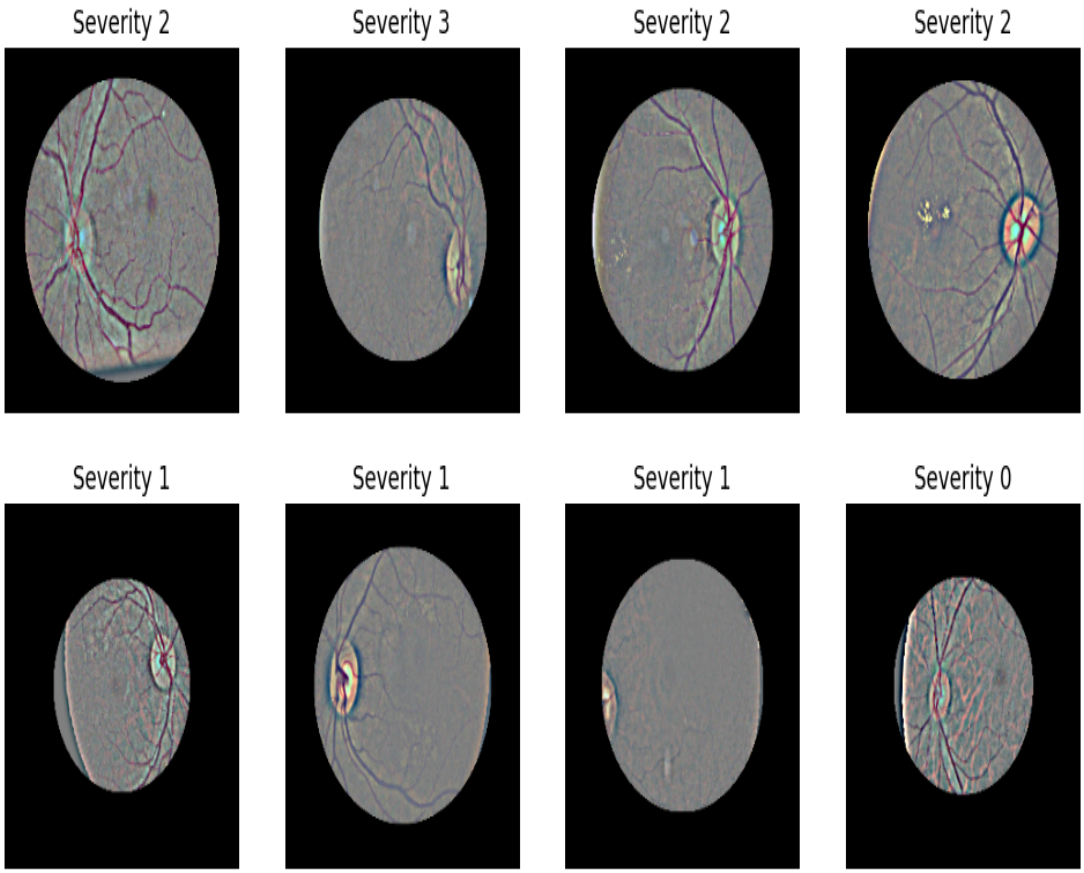

Figure 4.12: Ben Graham's processing image

4.5.3 Implication of Modified Preprocessing

The modified preprocessing takes the idea of contrast enhancement from CLAHE and apply it on the green channel of the image and enhance the edges using Ben Garham's kernel and standardized the image by clipping with circular mask similar way as Ben Graham proceeded.

First green channel is extracted from the input image. Then CLAHE is applied on the green channel of the image. It enhance visual contrast by localizing the pixel intensities. For medical imaging task it proves to be beneficial as here even the minute features imply meaning. Parameters that controls the CLAHE settings are respectively Clip limit 2.0 and 8x8 tile grid size.

The image is then cropped into a circular form with a radius of 90% of its original size. This stage eliminates boundary effects from the picture and standardizes its dimensions for future processing. It is done by creating a circular mask which keeps the center part while removing the outer 10%.

To remove the noise, a Gaussian blur kernel is applied with size (3,3) and standard deviation of 10. This procedure smoothens the image and reduces noise.

After this a kernel matrix of size [-1, -1, -1; -1, 9, -1; -1, -1, -1] applies to the image, which will enhance the edges of the image.

The aim of this preprocessing is to improve the quality of the eye fundus image for the diagnosis of diabetic retinopathy.

Mathematical formulation of Modified processing

Preprocessing steps	Mathematical formulation
1. Compute the histogram of the green channel image ranging from 0-255	$H(k) = \sum_{x=1}^{M} \sum_{y=1}^{N} \delta(I_g(x,y) - k)$
2. Convert green channel to 8 bit unsigned integer	$G_{8u}(x,y) = \text{round}\left(\frac{255 \times G(x,y)}{\max(G)}\right)$
3. CLAHE function	The CLAHE transformation $T(i)$ is given by: $T(i) = \frac{\text{clip}(h(i))}{\sum_j h(j)} \times (L-1)$
4. CLAHE on the green channel	$G_{\text{CLAHE}}(x,y) = \begin{cases} \text{HE}(G(x,y)), & \text{if } H(G(x,y)) \leq \text{clipLimit} \\ G(x,y), & \text{otherwise} \end{cases}$
5. CLAHE apply on the image	$G_{\text{CLAHE}}(x,y) = \text{CLAHE}(G_{\text{original}}(x,y), \text{clipLimit} = 2.0, \text{tileGridSize} = (8,8))$
6. Convert to float32	$I_{\text{CLAHE, float32}} = \text{astype}(I_{\text{CLAHE, 16u}}, \text{float32})$
7. Convert Grayscale back to RGB	$I_{\text{RGB}}(x,y) = [I_{\text{gray}}(x,y), I_{\text{gray}}(x,y), I_{\text{gray}}(x,y)]$
8. Ben graham's kernel	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$
9. Gaussian Blur	GaussianBlur(img,(3,3),10)

Figure 4.13: Modified processing

Modified preprocessing images

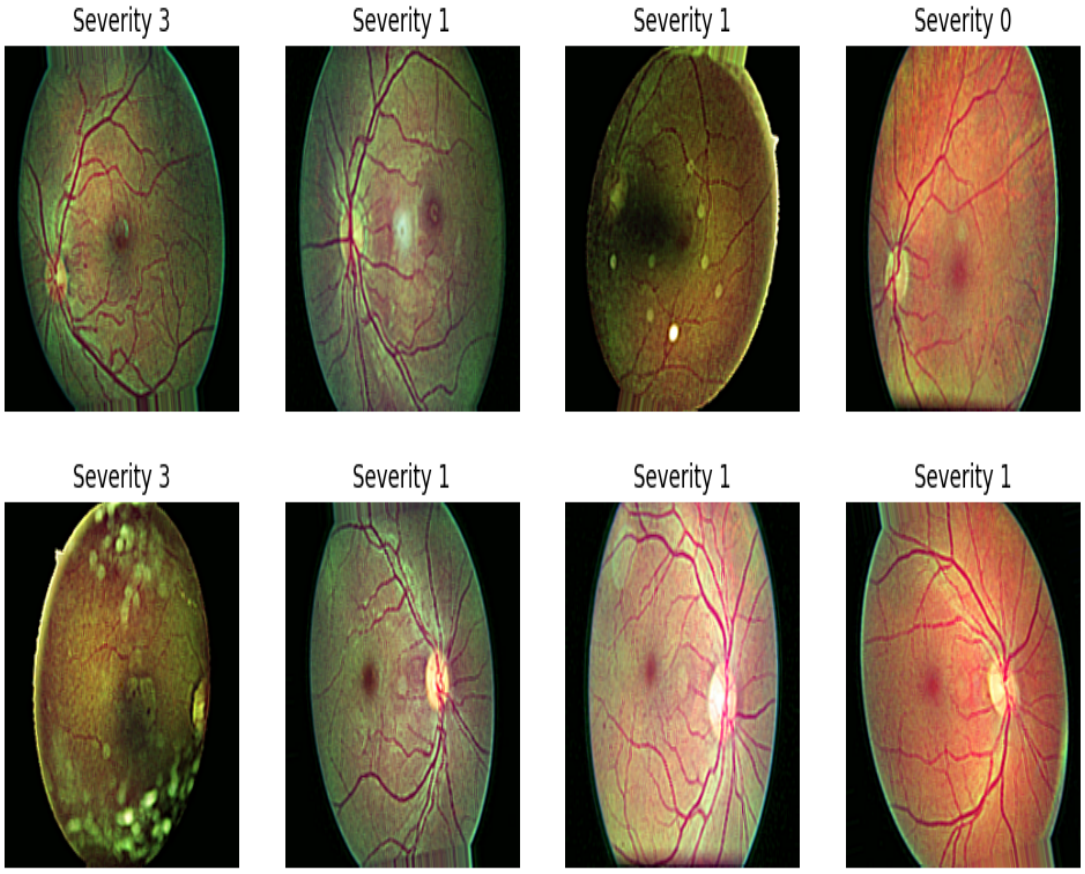

Figure 4.14: Modified preprocessing images

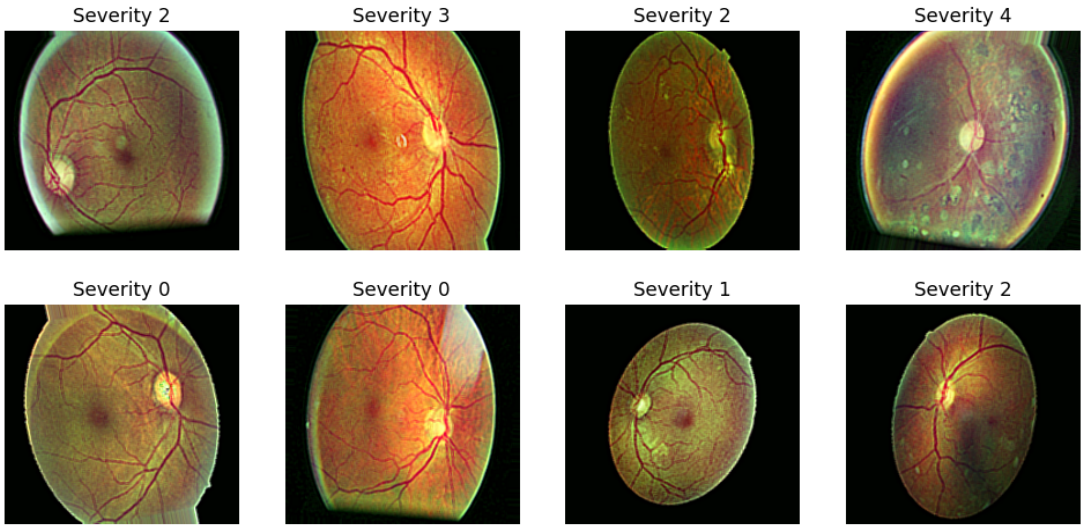

Figure 4.15: Modified preprocessing images

4.6 Design and Implementation

The selection of base models is crucial in designing and implementing an accurate diabetic retinopathy detection system employing an ensemble model. In this technique, we combine the characteristics of several convolutional neural network designs, such as InceptionV3, ResNet50, EfficientNetB5, and DenseNet169, to increase the detection system's accuracy and resilience.

The goal of the ensemble model is to produce better performance in identifying diabetic retinopathy by combining the predictions of these several base models and taking use of their complimentary capabilities. Each base model contributes unique architectural elements and learning capabilities to the ensemble, allowing for a more thorough study of retinal fundus pictures.

The ensemble strategy used here is Stacking. here pretrained models are stacked to improve to acheive ensemble model. Stacking uses the predictions of individual base models as input characteristics for the meta-learner, which is often another neural network or a machine learning algorithm. This meta-learner then gives the final output using the combined predictions of the underlying models.

Moreover in the application stage transfer learning is widely used to speed up model training and enhance performance. Transfer learning entails utilizing existing models trained on extensive datasets such, as ImageNet to set the initial weights of the foundational models. These pre trained models have acquired feature representations from a volume of data, which can be adjusted for better accuracy, in detecting diabetic retinopathy with a smaller dataset.

By fine-tuning the pre-trained models, base models may tailor their learnt representations to the requirements of the diabetic retinopathy detection problem, resulting in increased performance and convergence during training. By combining ensemble learning with transfer learning, the detection system excels in accuracy, robustness, and generalisation capabilities than individual models by using the collective intelligence of numerous base models through ensemble learning.

4.6.1 System Workflow

Workflow

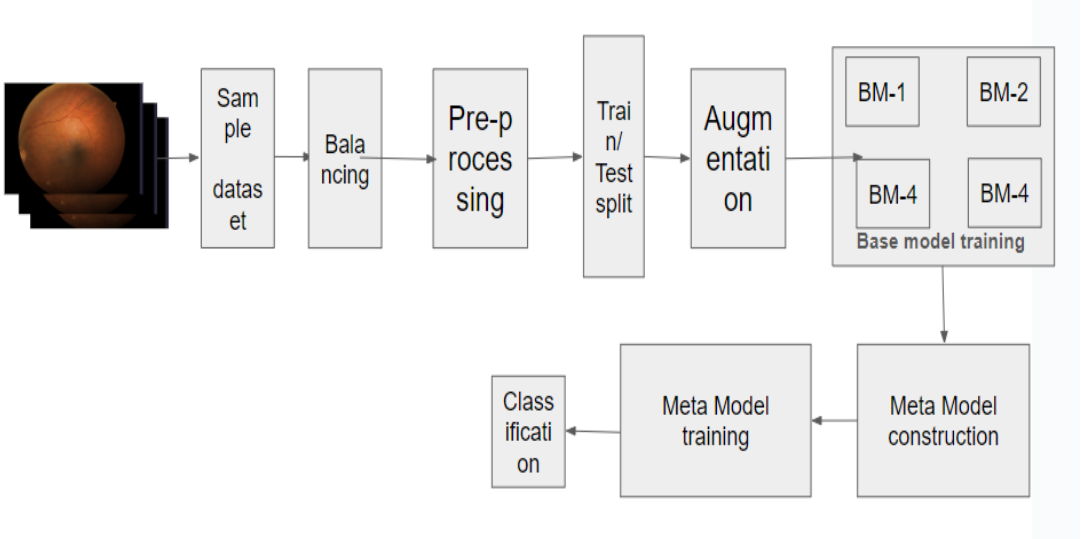

Figure 4.16: Workflow

The process of developing the ensemble model to predict DR from a smaller Kaggle EyePACS dataset as a subsample can be divided into several stages, including data acquisition, data pre-processing, data analysis, algorithm training, and algorithm testing. Here's a detailed breakdown of the entire system workflow:Here's a detailed breakdown of the entire system workflow:

1. Data Acquisition Dataset Source: The data is collected from Kaggle EyePACS competition which consists of more than 34,000 microscopic images of retinal images of varying degree of diabetic retinopathy. Subsampling: Because of the space limitation and computational requirements, a sub-set of about 8000 samples of pure images is extracted from the entire collection. We call this kind of subsample a training subsample, which forms a representative sample to train models.

2. Data Balancing Class Imbalance: In addition to it, the Eyepacs data is extremely imbalance and shows high bias toward some grades of diabetic retinopathy and some classes have very few cases. Balancing the Dataset: We balanced the 8000 images of the subsample. Created 830 images which are balancedly distributed among the grades, each class contains 166 images. It is done by a combined approach of oversampling and undersampling.

3. Data Preprocessing Preprocessing Steps: All images are processed through several preprocessing methods. These processes are explained briefly above. In this step, it is important to keep in mind that we're resizing images to 224X224 dimensions.

4. Train-Validation Split Splitting the Data: The data is nicely partitioned such that 80% is used for training purposes while the remaining 20% if for validation, Of which 664 images are used for training and 166 images for validation.

5. Data Augmentation Keras Image Generators: Training Generator: Trains the model using the augmented training set with rotation or flipping of the images to form a bigger set of images to avoid getting sucked into overfitting. Validation Generator: Validated the model using the validation set in cases where the augmentation was not used during the training phase.

6. Training Base Models Base Models Selection: Four of them out of the five selected models are as follows: InceptionV3, ResNet50, EfficientNetB5, and DenseNet169.

Model Customization: Removing Top Layers: This involves the deletion of specific layers from the image's classification layer model.

Adding New Layers: The base models are changed by adding new fully connected layers with softmax activation which enables the classification of the images into the five grades of diabetic retinopathy.

Training: Each base model is fine-tuned on the training set with the added softmax layers. The fixed learning rate of is 0. 001, with batch size of 32 and Adam optimizer to enhance the learning process for layers of networks with 20 epochs for InceptionV3 ResNet50, 10 epochs for EfficientNetB5 DenseNet169.

7. Creating the Meta Model Loading Trained Models: The four fine-tuned models for the base payload have been loaded. Removing Softmax Layers: The last softmax layers are removed which were produced during covering individual training. Extracting Latent Features: Features, that are used to make the final decision, are taken out from the penultimate layer (second last layer) of each base model. Concatenating Features: Inferred latent features from both the Collaborative Filtering model and the Contextual model are combined with the latent features from base models in a single tensor.

8. The meta model: Its construction and development New Dense Layers: New layers are added to continue to work on the concatenate features: A dense layer of 512 neurons that utilize ReLU activation with batch normalization and dropout nodes. The components of the system described above are a 256-neuron dense layer with similar properties. The last layer is fully connected, commonly known as the softmax layer to output probability distribution between the five given grades. Freezing Base Model Layers: The layers of the base models become locked down or fixed in order to preserve their learned features while training for additional dense layers.

Multi-Input Generator: There is a generator trained in each case while the four basic generators deliver input batches in parallel.

Training the Meta Model: The meta model is trained for 60 epoch using multi input generator where the new dense layer has been added and need to be trained, however the basic layer of the base model are retained as are.

9. Classification and Evaluation

Classification: The training of the meta-model allows for predicting the grade of diabetic retinopathy of the validation set. Evaluation: Different evaluation criteria like accuracy, precision, recall, and F1-score are employed to check the efficiency of developed models to detect DR in diabetic patients.

This concern summarises an entire pipeline including data gathering, data preparation, training an individual model and combining the predictive models to form an efficient system for detecting diabetic retinopathy.

4.7 Model Architecture

The architecture of the suggested ensemble model is carefully constructed to guarantee high accuracy and strong resistance to diabetic retinopathy identification instabilities. The approach uses several deep learning models and applies them together aiming at taking advantage of their performances in order to create an efficient system of prediction. To elaborate, the principal structural elements are base models, a meta-learner, and the use of transfer-learning approaches.

Base Models

InceptionV3: Finally, InceptionV3 is well-liked for its quick computation and high precision The architecture is based on the factorized convolutions and the advanced level of regulation. This architecture incurs many layers of filters of different measures to be able to detect a broad spectrum of features on different scales.

ResNet50: ResNet50 presents residual connections these aid in learning very deep networks since they neutralize the vanishing gradient problem. These connections enable the model to learn the mapping between the identity matrices and the latent variables to achieve faster convergence of the cost function and better accuracy.

EfficientNetB5: EfficientNetB5 increases the network width, depth, and resolution, following a structured approach while enhancing the proposed framework's accuracy and efficiency. Due to the reduced complexity of the model, and since it also works efficiently with less parameters, it boasts a top-notch performance compared to other architectural models.

DenseNet169: Compared to most convolutional networks, DenseNet169 has feed-forward connections in layers which link each layer to all the other layers enhancing the flow of gradients through the network. This makes the connectivity pattern dense which in turn brings fewer cases of the vanishing gradient problem and helps in the reuse of features hence improving the performance of the model.

Stacking and Meta-Learner

The ensemble strategy is about using these base models together By applying the stacking on these base models, a sophisticated and adaptive detection system can be created. Using the outcomes from the base models as input features, the meta-learner model can work. Often, a meta-learner can be quite a different model, for instance, a logistic regression classifier or another neural network. Some of the types of models include: The meta-learner is learned to discover the best way of blending the predictions of the base models to make the decision. It is done based on the stacking process and enables the ensemble method to guess based on the strengths of the base models.

Ensemble model

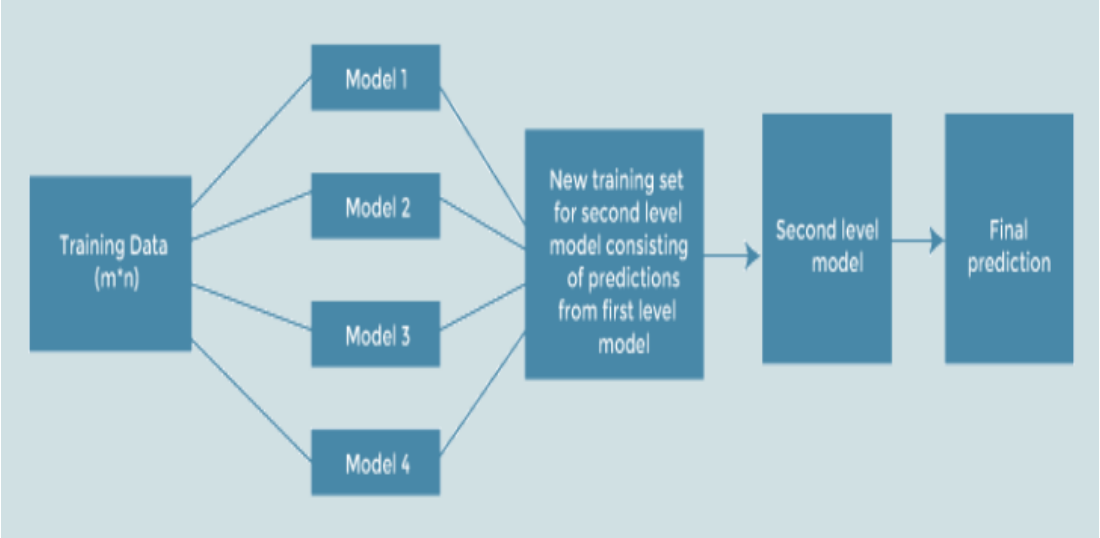

Figure 4.17: Ensemble Model

4.7.1 Base Model Architecture and Training strategy

In this ensemble model, we utilize four advanced convolutional neural network (CNN) architectures: They are InceptionV3, ResNet50, EfficientNetB5, and DenseNet169. Both models are then fine-tuned on a diabetic retinopathy dataset, but are initially trained on the ImageNet dataset that serves as a base for rich feature extraction and substantially enhances the accuracy of the diabetic retinopathy detection.

The general approach that is followed when working on each of the base models consist of the following: loading the pre-trained network, architectural alterations and finally fine-tuning of the network with the specific target dataset.We discuss how to load the pre-trained models and make changes to these models for our application.

First Loading Pre-Trained Models :The selected models include InceptionV3, ResNet50, EfficientNetB5, DenseNet169, which have weights pre-trained on Images from ImageNet. The first layer for each of the pre-trained models is for ImageNet classification task, which is the top layer in origin. Thus it is replaced to suit the requirements of the models for the diabetic retinopathy classification task which consists of 5 classes corresponding to various stages of the disease.

Add Additional Layers:

Once the first layer is stripped off we replace it with more layers to tune the model with current problem.
GlobalAveragePooling2D: Blurs each feature map to one scalar value by averaging all the values of this map, which is digital dimensionality reduction that preserves essential information.
Dense Layer (1024 units): New layer: Add fully connected layer with 1024 neurons and ReLu activation function, to prevent overfitting – L2 regularizer.
BatchNormalization: Reduces the volume and variability of the data, and speeds up the training process for the next layer.
Dropout (0. 2): The fourth option is even more rigorous and excludes a random 20% of neurons during the training phase as well, which helps prevent overfitting.
Dense Layer (512 units): Another one is a fully connected layer with 512 neurons, ReLU activation, and L2 regularization of weights applied.
BatchNormalization and Dropout: plied for regularization and stabilization once more.
Output Layer (5 units): A softmax layer with five neurons, this is because there are five classes involved in the classification of diabetes retinopathy, giving the class probability.

Training Procedure for Base Model

Compile the Model:

The model is compiled using the Adam optimizer and the learning rate is set to 0. 001. Thus, the Adam optimizer is selected due to its high efficiency and pertinent gradient sparsity property. The loss function used is categorical cross-entropy, because it is appropriate for techniques for multi-class classification problems. Training Settings:

Batch Size: 32. The recommended size of this batch ensures both that the memory usage is reasonable, and stabilization of incremental gradient uptakes.

Epochs:

InceptionV3 and ResNet50: After using 20 epochs as its training parameter. EfficientNetB5 and DenseNet169: They were trained for a total of 10 epochs. Because these models go deeper and are more intricate, it takes fewer epochs to fine-tune these models without compromising the model's accuracy and range.

Data Preprocessing and Augmentation:

Source images are then also scaled to the size 224x224 pixels as base models, especially in input acceptation. After that, the training for the CNN model begins by applying data augmentation including random rotations, flips, and zooms to the training data to enhance the ability of the detect the features from the input data.

Fine-Tuning:

At first, only the newly added layers are subjected to the training process leaving the pre-trained layers fixed or rather nontrainable. Once enough layers are appended the entire network including the base layers is trained on the Diabetic Retinopathy dataset. This is beneficial in that, the layers that were pre-trained retain the features learned from the ImageNet dataset while being adjusted according to the features of the new task at hand.

Ensemble Strategy There is an ensemble of fine-tuned base models used in this analysis, and the outputs from each of them are combined using a stacking approach.

The base model architectures are meticulously designed to enhance the performance of the final ensemble model.

Base Model Workflow

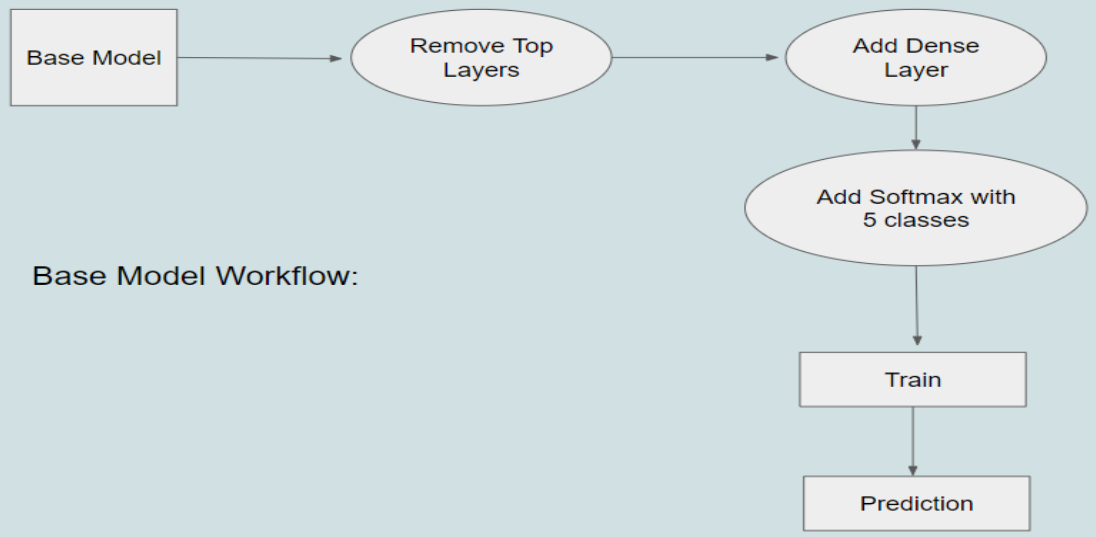

Figure 4.18: Base Model Workflow

4.7.2 Meta Model Architecture and Training strategy

Ensemble of deep neural network means multiple base models are framed to work together, and meta model implementing an ensemble of base models aims at enhancing the overall performance of classification. The following extracts gives a detailed explanation on how the meta model is constructed, along with the architecture of the model, and its working along with the training strategy using a multi-input generator.

Meta Model Architecture

Loading Base Models: The meta model first sets load pretrained base models, in this case being, Inception V3, ResNet 50, Efficient Net 5 and Dense Net 169. These models have been every trained in parallel on the diabetic retinopathy dataset have had their final layers (classification layers) stripped off to utilize their feature learning mechanism.

Renaming Layers: All the layers in the base models are re-named to eliminate naming conflicts that might arise when concatenating the layers from two models. This is even followed for each of the layers in each of the models where every layer is named following a prefix of the model type (example: 'resnet', 'inception').

Freezing Layers: To be able to extend the features learned from the base models themselves, all the layers in each base model are frozen. This makes a lot of sense in practice and its effect is to keep the weights of these layers constant while training the meta model.

Extracting Latent Features: The feature in the second last layer (penultimate layer) of every base model is used as 'Latent feature'. This is generally aligned with a coarser level of abstraction of the input image, that is, the image description for each pattern or feature relevant to the classification process.

Concatenation of Latent Features: The features from the penultimate layers of the four base models are combined together as one feature vector. It used a feature vector that integrates various representations of each base model, which improves the meta model prediction ability.

Fully Connected Layers: Concatenated features are transferred across Dense layers.

The first dense layer has 512 neurons with ReLU activation and L2 regularisation to prevent overfitting. It is followed by batch normalisation to stabilise and speed training, and then dropout at a rate of 0.5 to prevent overfitting.

The second dense layer consists of 256 neurons following same process as first dense layer.

Output Layer: The last dense layer is a softmax layer, which has the same number of neurons as classes (5 in this example, which correspond to the grades of diabetic retinopathy). This layer generates a probability distribution across the classes, allowing multi-class categorization.

Multi-Input Generator To make it possible to train the narmodel using multiple base models require the use of a special multi-input generator. This generator serves to agree on the stream of data with other inputs, feeding the same set of images to all base models at once. Here's how it works:

Synchronization: The generator acquires images and their labels for a batch and then sends the information to the category. This batch is then copied four times to feed the four base models. This is important so as to guarantee that the different base models realize similar input images so as to extract the features from.

Yielding Data: Some sketches of programs that the generator emits include a tuple that contains a list of inputs, where each base model has one input, as well as the target labels. This format is in accordance to the meta-model format which defines four inputs in separate parameters.

Training Strategy for Meta Model

1.Compilation:

The meta model is trained with the Adam optimizer, fixed learning rate of : 0.001, and Objective function: categorical-cross entropy. Some of the aggregates that are measured during training entail accuracy.

2.Training Process:

It involves the steps of fitting the meta model but using the custom multi-input generator to entail both the training and the validation datasets. The training of the model is performed for 60 epochs with batch size 6.

3.Freezing Base Model Layers:

Hence, freezing the layers belonging to base models brings the training on to the new added dense layers only. This approach provides a way to show how the meta-dictionary is learned or how the base model is trained to decide on the right way of merging the feature vectors output by the base models for better classification outcomes.

4.Validation:

In training, the model's outperform based on a different validation set called the validation set. This assists in the regularization used in checking overfitting and making the right adjustments to the parameters used in the model.

Meta Model Workflow

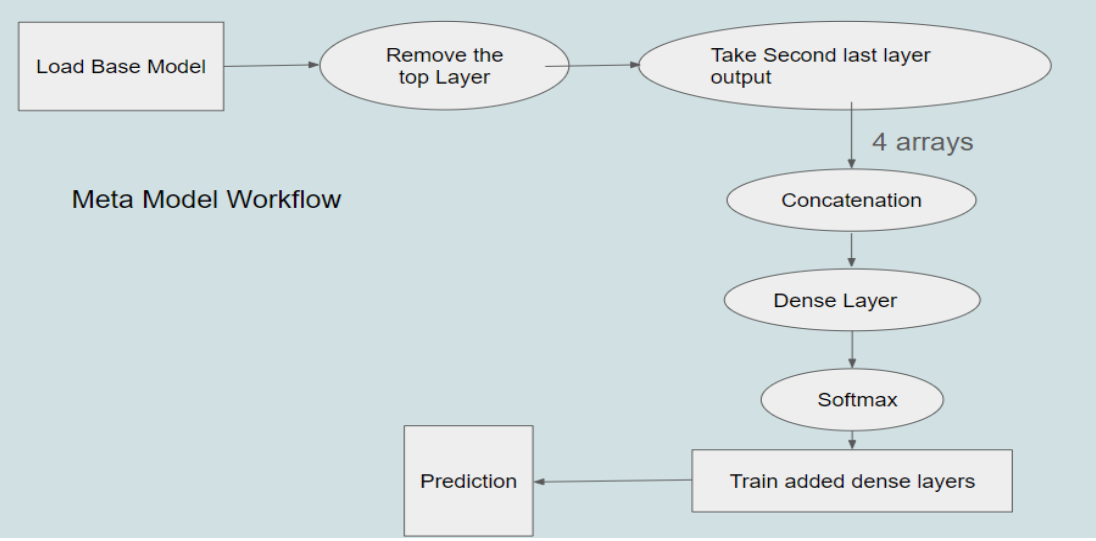

Figure 4.19: Meta Model Workflow

As noted earlier, there are several benefits of using Meta Model, which can be elaborated as follows: Improved Accuracy: The meta model contain multiple base models to cover as many features as possible therefore provide a better solution to detect Diabetic retinopathy. The Model is Robust against variations of data. The model will be generalized to handle various feature

vectors.

The meta model, built as an ensemble of InceptionV3, ResNet50, EfficientNetB5, and DenseNet169, significantly enhances the detection accuracy of diabetic retinopathy.

Chapter 5

Evaluation and Discussion

The objective of this study's outcomes evaluation is to give insights into the performance of the trained model with different preprocessing techniques while taking into account the limits and settings under which the model is trained. While the stated accuracy for the model trained on a subsample of 166 photos per class appears poor, it is critical to contextualize these findings given the experiment's limits.

The model was trained using a subset of the dataset that had 830 photos, with only 166 images accessible for each class owing to resource constraints. This small sample size may hinder the model's capacity to generalize successfully to previously unknown data, especially when dealing with complicated patterns or subtle characteristics seen in retinal pictures.

5.1 Evaluation Metrics used:

Accuracy
Accuracy is the most intuitive metric, representing the overall correctness of the model's predictions. It's calculated as the ratio of correctly classified instances to the total number of instances.
Accuracy = (True Positives + True Negatives) / Total Samples
Precision
Precision measures the accuracy of the positive predictions. It is the ratio of correctly predicted positive observations to the total predicted positives.
Precision = True Positives / (True Positives + False Positives)
Recall
Recall, also known as sensitivity, emphasizes completeness. It measures the proportion of true positives the model identified out of all the actual positive cases.
Recall = True Positives / (True Positives + False Negatives)
F1-score
F1-score provides a harmonic mean, balancing both Precision and Recall. It considers a model's ability to both correctly identify positive cases (recall) and avoid false positives (precision).
F1-score = 2 X(Precision X Recall) / (Precision + Recall)
True Positive rate
True positive also refers to sensitivity or recall, it represents the proportion of actual positive cases the model correctly identified.
TPR = TP / (TP + FN)
False Positive rate
It represents the proportion of negative cases the model incorrectly classified as positive.
FPR = FP / (TN + FP)
False Negative rate
It shows how often a model misses actual positive cases.
FNR = False Negatives / (True Positives + False Negatives)

5.2 Result Evaluation

5.2.1 Result evaluation on applying CLAHE image processing

Classes of DR	Precision	Recall	F1-score
DR-0	0.48	0.42	0.43
DR-1	0.34	0.33	0.33
DR-2	0.40	0.40	0.38
DR-3	0.40	0.40	0.38
DR-4	0.40	0.40	0.38

Table 5.1: Evaluation of CLAHE preprocessing techniques applied

Total Avg Accuracy for CLAHE = 0.42
Confusion matrix of model applying CLAHE

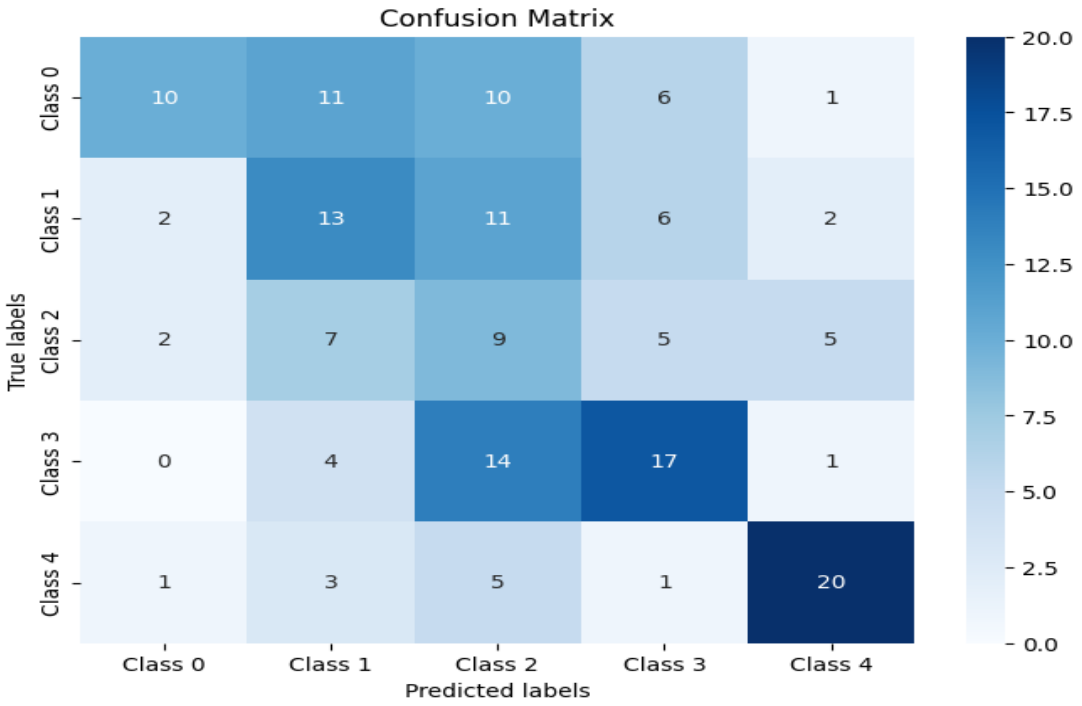

Figure 5.1: Confusion matrix of model applying CLAHE

ROC curve for Model applying CLAHE

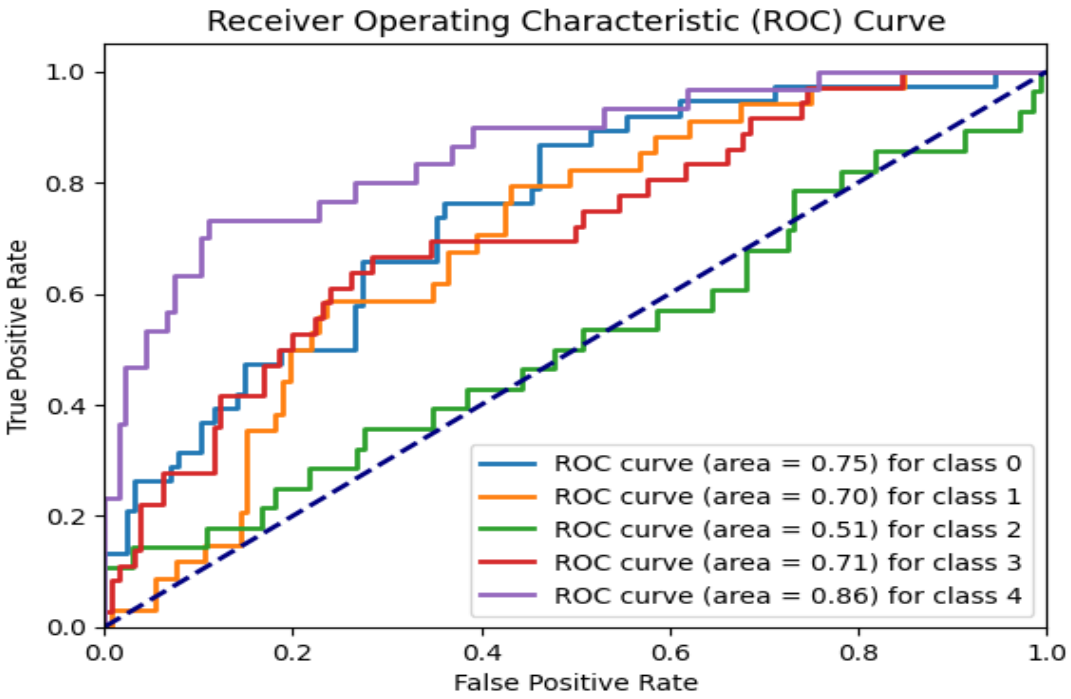

Figure 5.2: ROC curve for Model applying CLAHE

From the ROC curve it is clearly seen that CLAHE showing low accuracy result detecting Class-2 DR(Mild DR). However, from confusion matrix, it is clear that it showing comparetively better result in class-0 DR, as most of the results for class 0 are distributed along class 0 class 1 and class 2 . It indicates Severely wrong detection for mild class DR using CLAHE.

DR-4 (proliferative DR) evaluation by CLAHE True Positives (TP): 20 images correctly detected as class 4.

False Negatives (FN): Class 4 images detected as other classes: Detected as class 3: 1 Detected as class 2: 5 Detected as class 1: 3 Detected as class 0: 1 Total FN for class 4 = 10

Total True positive Rate for class 4 applying CLAHE= 0.67

Total False Negative rate for class 4 applying CLAHE= 0.33

This implicates a high efficiency in Class 4 DR (Proliferative) detection using CLAHE but also implying a not ignorable amount of false negative rate. It is essential to detect Class 4 DR immediately as delay can lead to vision loss of patient. So there is a room for improvement detecting Proliferative DR using Preprocessing technique CLAHE.

5.2.2 Result Evaluation on applying Ben Graham's Preprocessing

Classes of DR	Precision	Recall	F1-score
DR-0	0.29	0.20	0.24
DR-1	0.26	0.32	0.29
DR-2	0.18	0.21	0.19
DR-3	0.36	0.39	0.37
DR-4	0.58	0.50	0.54

Table 5.2: Evaluation of Ben Graham's preprocessing techniques applied

Total Avg Accuracy for Ben Graham's = 0.33

Confusion matrix of model applying Ben Graham's

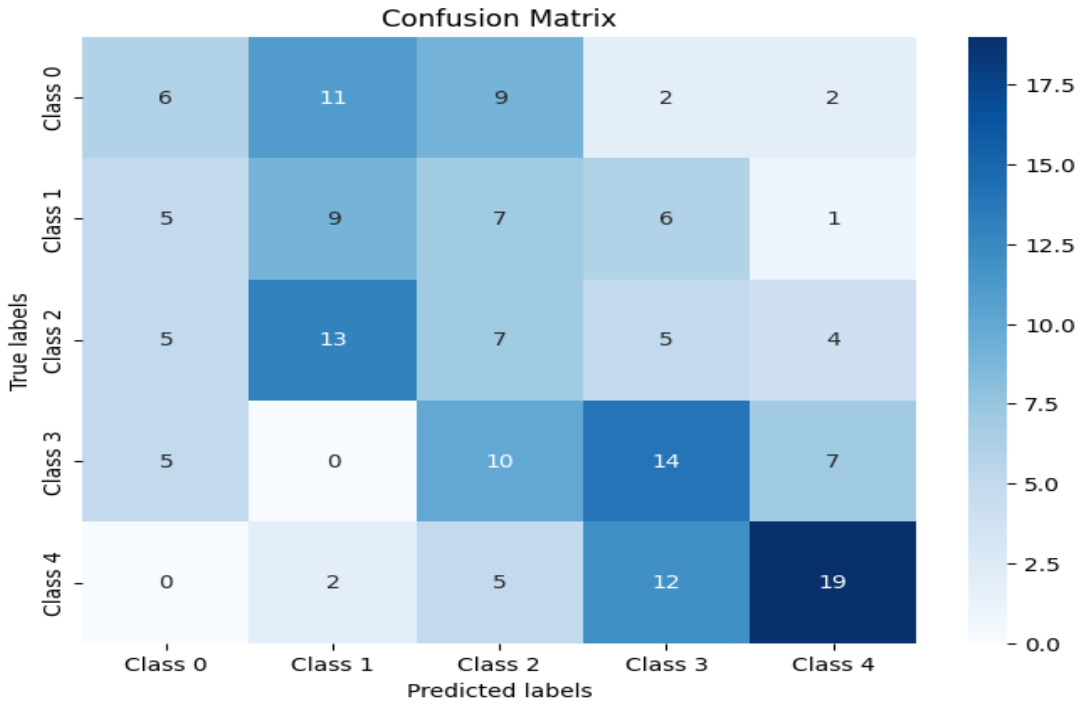

Figure 5.3: Confusion matrix for model applying Ben Graham's

ROC curve for Model applying Ben Graham's

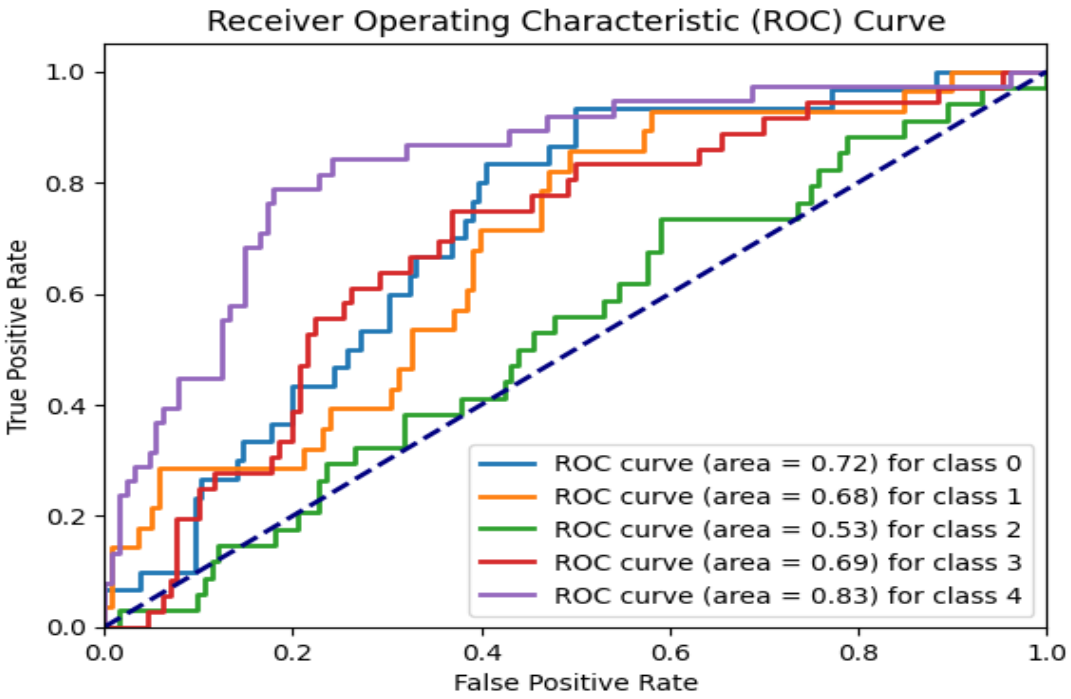

Figure 5.4: ROC curve for Model applying Ben graham's

From the ROC curve it clearly depicts that, Ben Graham show surprisingly better results for Class-4 (Proliferative DR) detection. In their experiment accuracy is impacted by the image resolution and the low epochs for the training of models. It shows a better result when a (512X512) resolution image is used, here at the end of this section including an example of using (512X512) dimension image on Ben Graham's processing.

Class 4 Evaluation applying Ben Graham's Processing True Positives (TP): 19 images correctly detected as class 4.

False Negatives (FN): Class 4 images detected as other classes:

Detected as class 3: 12

Detected as class 2: 5

Detected as class 1: 2

Detected as class 0: 0

Total FN for class 4 = 19

The model performs relatively well for Class 4 images with a TPR of 0.50. However, it still has a considerable false negative rate (FNR) of 0.50, indicating that while the model can detect half of the severe cases, it misses the other half.

5.2.3 Result Evaluation on Modified preprocessing

Classes of DR	Precision	Recall	F1-score
DR-0	0.40	0.29	0.34
DR-1	0.33	0.07	0.12
DR-2	0.23	0.34	0.27
DR-3	0.46	0.69	0.56
DR-4	0.51	0.49	0.50

Table 5.3: Evaluation of Modified preprocessing techniques applied

Total Avg Accuracy for Modified preprocessing = 0.40

Confusion matrix of model applying Modified preprocessing

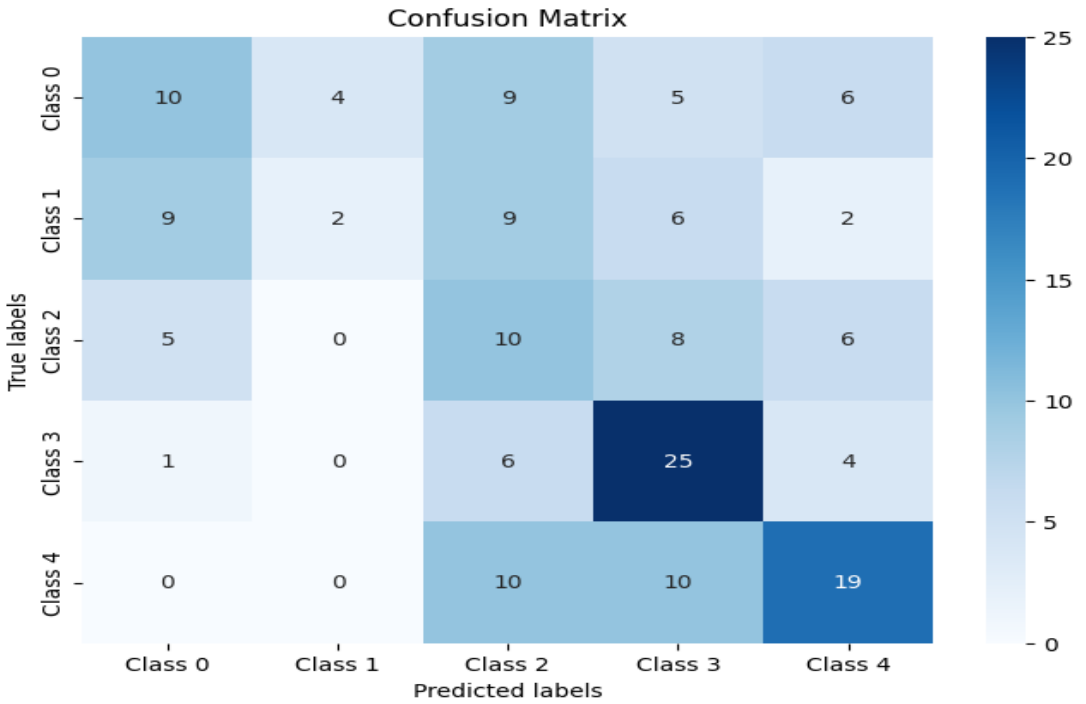

Figure 5.5: Confusion matrix for model applying Modified Preprocessing

ROC curve for Model applying Ben Graham's

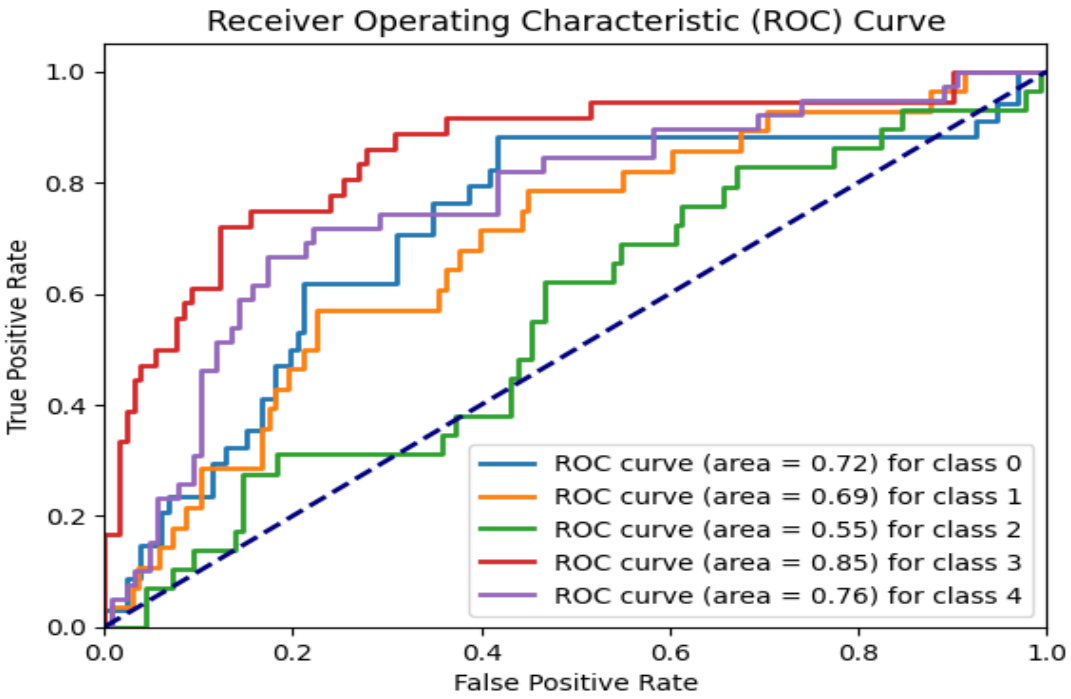

Figure 5.6: ROC curve for Model applying Modified preprocessing

The ROC curve shows a high accuracy for class-3 and Class 4 DR images.

Class 4 Evaluation applying Ben Graham's Processing True Positives (TP): 19 images correctly detected as class 4.

False Negatives (FN): Class 4 images detected as other classes:

Detected as class 3: 10

Detected as class 2: 10

Detected as class 1: 0

Detected as class 0: 0

Total FN for class 4 = 20

This Preprocessing technique performs relatively well for Proliferative DR or class-4 DR detection. Though there is a significant amount of class-4 image detected as class 2 and class 3, but amount of image detected as class 0 and class low is negligible, which depicts the preprocessing techniques perform well in detecting severe DR.

Using Ben Graham's preprocessing in (512 X 512) dimension images shows a better performance: Here the ensemble model is trained for 10 epochs only.

5.2.4 Ben Graham's processing on high dimension image set

Confusion matrics of model applying Ben Graham's using (512X512) image set:

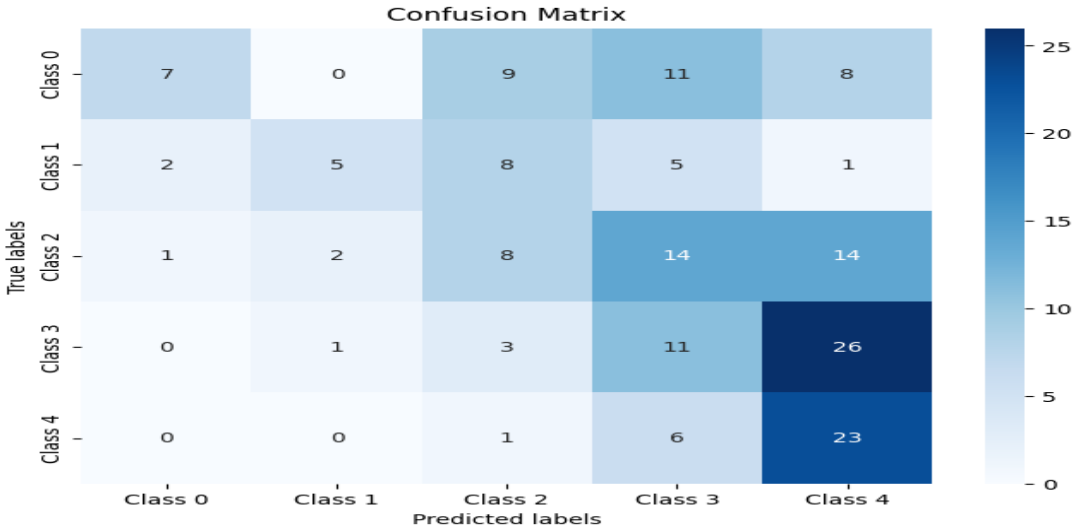

Figure 5.7: Confusion matrix of model applying Ben Graham's using (512X512) image set:

This work shows using high-resolution image size the performance of Ben Graham's significantly increase for Proliferative DR. Here the Model is trained for 10 epochs.

5.3 Comparison on Preprocessing techniques used

Preprocessing methods are critical in medical image analysis because they improve picture quality and can have a major influence on the performance of deep learning models.This study analyses three preprocessing techniques: CLAHE (Contrast Limited Adaptive Histogram Equalisation), Ben Graham's preprocessing, and a modified preprocessing strategy, with an emphasis on how they affect Ensemble model performance in terms of precision, recall, F1-score, and accuracy.

Approach	Precision	Recall	F1-score	Accuracy
CLAHE Preprocessing	0.48	0.42	0.43	0.42
Ben Graham's Preprocessing	0.34	0.33	0.33	0.33
Modified Preprocessing	0.40	0.40	0.38	0.40

Table 5.4: Evaluation of different preprocessing techniques applied

CLAHE Processing

CLAHE improves picture contrast by adaptive histogram equalisation, which modifies an image's contrast based on its immediate neighbourhood of pixels. This strategy is especially useful in medical imaging, as in medical image analysis the minor details are not negotiable. In this investigation, the CLAHE preprocessing method has a precision of 0.48, recall of 0.42, F1-score of 0.43, and accuracy of 0.42.

CLAHE significantly enhances the contrast of retinal images, making it easier to distinguish between different regions and abnormalities. Unlike global histogram equalization, CLAHE works on small regions in the image, preserving the details and reducing the risk of noise amplification. However, the process can be computationally intensive, especially when dealing with high-resolution images. There is also a risk of over-enhancing certain features.

Ben Graham's Processing

Ben Graham's preprocessing method standardises the image by scaling it to a certain radius, removing the local average colour, and clipping it to remove border effects. Ben Graham's processing increases the image's structural intricacies and clarity. The performance measures for this approach were 0.34 precision, 0.33 recall, 0.33 F1 score, and 0.33 accuracy. But using high-resolution images the accuracy increases significantly.

This technique is particularly good for detecting Severe DR images. The preprocessing steps are relatively complex and might require fine-tuning for optimal results. Compared to CLAHE, this method might not enhance the contrast as effectively, potentially leading to lower performance in detecting subtle features.

Modified Preprocessing

The Modified preprocessing approach combines elements of both CLAHE and Ben Graham's methods, aiming to balance contrast enhancement with structural clarity. This technique achieved a precision of 0.40, recall of 0.40, F1-score of 0.38, and an accuracy of 0.40.

This method bridge a gap between enhancing contrast and maintaining structural details, which can be beneficial for comprehensive analysis.The effectiveness of this approach depends heavily on the correct tuning of parameters, which can be challenging and time-consuming.

Comparison

When comparing these three strategies, it is clear that each has benefits and disadvantages. CLAHE preprocessing, with the highest accuracy and F1-score, is very good at increasing contrast and making minor characteristics more visible. However, CLAHE preprocessing provides high accuracy for proliferative DR, it tends to result in false negatives distributed among the mild DR cases, posing a risk in early-stage diagnosis.

Ben Graham's preprocessing excels at edge enhancement and size standardization but demonstrates worse performance metrics compared to the other methods. This is presumably because of less effective contrast enhancement and the low resolution of the training images. Its effectiveness increases significantly with higher-resolution images, indicating its potential utility under specific conditions.

The Modified preprocessing strategy shows comparatively better results with false negatives for proliferative DR distributed among only the severe grades. This makes it a safer option in critical diagnostic contexts where the early detection of severe DR is crucial.

5.4 Discussion

The results of this study highlight the nuanced trade-offs between preprocessing techniques and their impact on the performance of an ensemble model for diabetic retinopathy (DR) detection. The choice of preprocessing strategy has a considerable influence on the performance of deep learning models in medical image analysis. While CLAHE preprocessing appears to be the most promising in this investigation, the false negatives of proliferative DR for CLAHE, predominantly distributed among mild DR cases, pose a diagnostic challenge. Conversely, Ben Graham's preprocessing method, though less effective in performance metrics at lower resolutions, significantly improves with higher-resolution images, making it an excellent choice for edge enhancement and size standardization. The Modified preprocessing strategy is also a feasible choice, particularly when a balance of contrast and structural information is necessary. Future research might concentrate on further optimizing current strategies or inventing new methods to improve the accuracy and reliability of medical image analysis models. This includes focusing on enhancing preprocessing techniques to reduce false negatives across all DR stages, ensuring more reliable and comprehensive diagnostic tools.

The ensemble model, combining Inception V3, ResNet50, EfficientNetB5, and DenseNet169, underscores the benefits of integrating multiple architectures to harness diverse feature extraction capabilities. This approach enhances diagnostic accuracy and robustness but also introduces increased computational complexity and training time. The ensemble model's ability to aggregate various perspectives provides a comprehensive understanding of retinal images, which is crucial for reliable DR detection. Future work should aim to refine these preprocessing techniques and optimize the ensemble framework to mitigate false negatives across all DR stages, ensuring a more robust and efficient diagnostic tool.

Chapter 6

Conclusion

In this work, we conducted an ablation study to evaluate the effectiveness of various preprocessing techniques for diabetic retinopathy (DR) detection using an ensemble model. The preprocessing techniques examined include CLAHE (Contrast Limited Adaptive Histogram Equalization), Ben Graham's preprocessing method, and a modified preprocessing technique combining the contrast enhancement of CLAHE with the standardization of Ben Graham's process. The ensemble model leveraged the strengths of four state-of-the-art convolutional neural networks: Inception V3, ResNet50, EfficientNetB5, and DenseNet169.

Our results indicate that CLAHE preprocessing provided the best overall performance in terms of precision, recall, F1-score, and accuracy. However, it exhibited a concerning rate of false negatives, particularly in detecting various stages of DR. This limitation poses a significant risk in medical diagnostics, where missed diagnoses can have serious repercussions. Conversely, the modified preprocessing technique demonstrated a more balanced performance across all DR stages, especially for proliferative DR. It reduced the false negatives by distributing misclassifications more evenly across the severe categories, thus offering a safer alternative in critical diagnostic applications.

Ben Graham's preprocessing method, while generally performing below CLAHE and the modified technique at standard resolutions, showed exceptional results when applied to images with a 512x512 resolution. This highlights the importance of image resolution in preprocessing effectiveness and suggests that Ben Graham's technique may be more suitable for higher-resolution image data.

In conclusion, while CLAHE preprocessing shows promising overall accuracy, its tendency for false negatives necessitates caution. The modified preprocessing technique offers a balanced and safer approach for DR detection, particularly for more severe cases. Ben Graham's method excels with higher-resolution images, indicating its potential under specific conditions. Future work should focus on optimizing preprocessing techniques in conjunction with high-resolution images and further enhancing the robustness of ensemble models to minimize diagnostic errors.

6.1 Scopes for improvement

There's a great scope for enhancing the ensemble model's performance by incorporating some vision to it. To enhance the efficiency of an ensemble model for medical image diagnosis, several modifications can be made.

Selecting base models has a crucial impact on the performance of the ensemble model. By combining high throughput models we can enhance the performance of the ensemble model.

This work doesn't implement segmentation in feature extraction. There is a scope for implementing Segmentation for feature extraction, which may result high accuracy. This model is trained on a limited amount of data because of inefficient Hardware support.

Implementing the Attention mechanism in Ensemble model, we can generate an attention map, which will enhance the interpretability of the model.

Performing this work in high-performing hardware setup will result in great accuracy in the classification of DR. Taking High-Resolution Images as (512,512) has proven to be better accuracy than (224,224) images.

6.1.1 Limitations of the project work

The project only works with a subsample of the dataset containing about 8K images, so it might suffer from limited sample variance and does not cover all variety and intricacies of realistic medical-images. As it stands, it may be necessary to gather more data that is diverse enough to prevent evaluation inaccuracy. Despite the attempts to achieve balance within

the dataset, some of the classes may be missing, and the model may favor specific classes by achieving higher accuracy scores on them while the accuracy of accurate calculations for minority classes may be lower.

The specific experiment of training multiple deep learning models and an ensemble model is found to consume substantial resources in terms of GPUs and training time. This is often a challenge in places where the capacity to implement new programs is a challenge due to lack of capacities. The assumption of multiple deep networks, especially during inference, may result in increased costs in terms of computational power, thus reducing the real-time usability of ensemble models in clinical practice.

Deep learning models and specially generated ensembles are weak for their lack of explainability. This is why, when it comes to medical applications, the process by which such models make decisions should be made clear and transparent to promote clinician trust and avoid any form of tendency. An example of this argument refers to the transfer learning from previous models, where this practice could not include all the specific features of interest in medical imaging. Adjustment on medical images is required to ensure the model provides accurate results but may be constrained by the labeled medical images.

It is significant for the model to have extensive validation in the clinical environment to determine its real-world relevance. This is due to the fact that scientific methodologies usually involve controlling all the factors within experimentation, and the settings used in clinical practices are considerably diverse and complex.

6.2 Future Direction

The Kaggle Eyepacs dataset shows a great disparity between the mild DR and the Severe grade 3 and grade 4 DR. There's a great scope for implementing a generative adversarial network or variational auto encoder to synthetically generate grade 4 and grade 3 DR images.

As in recent times, it has been proved that Transformer architecture shows an exceptional performance in classifying different types of DR images. In the Future, Implementing Vision Transformer architecture on this problem with efficient Data processing will be a great area of research.

Although, this work deep drive to some of effective preprocessing techniques for DR detection, but the result is still not meeting expectations. There's an extensive need for more comprehensive research on efficient preprocessing technique for medical imaging.

Since not all features contribute to the detection problem, so there's a great need for research on applying attention mechanism to the feature map to give a certain attention to some unique features, that contribute heavily to the detection problem.

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