DIABETIC RETINOPATHY PREDICTION USING MULTI MODEL ALGORITHM WITH COMARISON STUDY

A PROJECT REPORT

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of

BACHELOR OF ENGINEERING

IN

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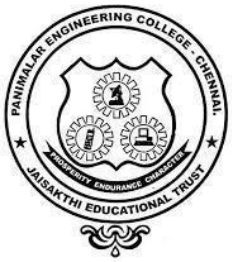

PANIMALAR ENGINEERING COLLEGE

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BONAFIDE CERTIFICATE

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ABSTRACT

Diabetic retinopathy (DR) is a prevalent and debilitating condition that affects millions of people worldwide. It is an eye complication that can occur in individuals with diabetes, resulting from the impairment of blood vessels located in the retina, which is the light-sensitive layer positioned at the back of the eye. Early detection and treatment of DR are crucial to prevent vision loss and improve patient outcomes. However, the traditional method of DR detection using manual inspection of fundus photographs by ophthalmologists is time-consuming and subjective. Recent advances in computer vision and machine learning have led to the development of automated algorithms for DR detection using retinal images. However, most existing algorithms rely on a single model, which can limit their accuracy and applicability in clinical settings. Here, a deep learning-based algorithm for DR detection that uses only fundus photographs is proposed.

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LIST OF ACRONYMS AND ABBREVIATIONS

DR	Diabetic Retinopathy
CNN	Convolutional Neural Network
VGG	Visual Geometric Group
ResNet	Residual Neural Network
NPDR	Non-proliferative diabetic retinopathy
PDR	Proliferative diabetic retinopathy

CHAPTER 1
INTRODUCTION

1.1 Introduction

The World Health Organization (WHO) states that diabetic retinopathy is the primary cause of blindness for individuals aged 20-64 years who are still working worldwide. In 2017, approximately 4.2 million individuals were blind due to diabetic retinopathy, while another 98 million experienced moderate to severe visual impairment. A study published in the Indian Journal of Endocrinology and Metabolism in 2016 revealed that diabetic retinopathy's occurrence in India is approximately 21.7%.

Furthermore, the study also found that the prevalence of diabetic retinopathy increases with the duration of diabetes and that individuals with poor glycemic control are more prone to develop diabetic retinopathy. Another study published in the Indian Journal of Ophthalmology in 2019 reported that diabetic retinopathy is the top reason for blindness in India, accounting for almost 6% of all blindness cases. The study also found that the incidence of diabetic retinopathy is higher in urban regions than in rural areas, and that there is a lack of awareness and screening programs for the disease in several parts of the country.

Among working-age adults, Diabetic retinopathy is a leading contributor to vision loss and impaired eyesight. Detecting and treating diabetic retinopathy at an early stage is crucial to avoid vision loss. Different automated techniques have been suggested for diabetic retinopathy detection using fundus images, but they have some limitations regarding accuracy and computational efficiency. In recent times, there has been an increasing focus on the use of multi-modal algorithms for detecting diabetic retinopathy, which incorporate data from various imaging modalities such as fundus images and visual field data.

1.2 Diabetic Retinopathy

Diabetic retinopathy is an eye-related complication that arises from diabetes. It results from the damage of small blood vessels in the retina, which detects light and transmits signals to the brain. The damage is caused by high blood sugar levels, which can lead to fluid or blood leakage from the blood vessels or their closure, causing inadequate circulation and retina damage. This damage can result in visual issues or blindness, and diabetic retinopathy is one of the major causes of blindness among adults. However, with effective diabetes management and frequent eye check-ups, diabetic retinopathy can be prevented or controlled.

1.3 Types of Diabetic Retinopathy

There are two primary forms of diabetic retinopathy:

a.Non-proliferative diabetic retinopathy (NPDR): This is the initial stage of diabetic retinopathy that involves minor damages to the blood vessels in the retina. In this stage, the blood vessels weaken and start to leak, resulting in small amounts of fluid and blood seeping into the retina. This can lead to inflammation in the macula, which is responsible for sharp, central vision. With the progression of NPDR, the blockage of more and more blood vessels in the retina can deprive the retina of essential oxygen and nutrients.

b.Proliferative diabetic retinopathy (PDR): This is the advanced stage of diabetic retinopathy, where new blood vessels start to grow in the retina. These new blood vessels are delicate and can easily break, resulting in the leakage of blood and fluid into the vitreous, transparent gel-like substance in the eye. This condition can cause the vitreous to become hazy and contribute to vision loss. Additionally, the growth of new blood vessels can stimulate the formation of scar tissue, which can pull on the retina and lead to retinal detachment. PDR is more severe than NPDR and can result in greater visual impairment.

1.4 Causes of Diabetic Retinopathy

The damage to the blood vessels in the retina due to high blood sugar levels is the root cause of diabetic retinopathy. Although the exact mechanism behind how high blood sugar levels damage blood vessels is not fully comprehended, it is believed that chronically elevated blood sugar levels can result in alterations in the blood vessels that increase their susceptibility to leakage, blockage, or abnormal growth. There are additional risk factors that can contribute to the onset and advancement of diabetic retinopathy, including hypertension, high cholesterol, smoking, and having diabetes for an extended period.

1.5 Symptoms of Diabetic Retinopathy

In its early stages, diabetic retinopathy may not show any noticeablesymptoms. However, as the condition progresses, symptoms may include:

1. Blurred or fluctuating vision
2. Impaired color vision
3. Dark or empty areas in the field of vision
4. Floaters or spots in the vision

5. Difficulty seeing at night
6. Sudden loss of vision

1.6 Detection of Diabetic Retinopathy

Various techniques have been devised to identify diabetic retinopathy, including manual inspection by eye specialists and computer-based algorithms for image analysis. Nevertheless, these approaches have their limitations, suchas being prone to subjectivity and requiring high costs for manual inspection, and lacking accuracy and sensitivity for automated analysis.

Researchers have endeavored to overcome these obstacles by exploring the potential of multi-modal algorithms that amalgamate various imaging modalities and employ machine-learning techniques to enhance the accuracy and sensitivity of diabetic retinopathy detection. These algorithms can scrutinize images from diverse sources, such as fundus photographs and fluorescence angiography, in order to recognize and categorize different phases of diabetic retinopathy.

Diabetic retinopathy can be detected using deep learning technology that leverages computer vision methods to examine retinal images and detect signsof the condition. Deep learning algorithms can be trained on extensive sets of retinal images to recognize patterns and characteristics that signify diabetic retinopathy. By doing so, these algorithms can analyze new retinal images and classify them as normal or potentially indicative of the disease.

The process of manually interpreting images for diabetic retinopathydiagnosis can be time-consuming and the accuracy of the diagnosis may vary between different observers. To overcome this challenge, machine learning and deep learning algorithms have been developed to automate the detection of diabetic retinopathy.

The integration of multi-modal algorithms has emerged as a promising approach in diabetic retinopathy detection, with several studies reporting high accuracy and sensitivity rates. By leveraging information from diverse imaging techniques, these algorithms can enhance the early identification and treatment of diabetic retinopathy, potentially reducing the risk of vision impairment and blindness among diabetic patients

This article aims to provide an overview of the current state of the art in diabetic retinopathy detection using multi-modal algorithms. The article first discusses the different imaging modalities used for diabetic retinopathy detection and their advantages and limitations. It then presents a review of recent studies that have proposed multi-modal algorithms for diabetic retinopathy detection and compares their performance to traditional single- modal approaches. Finally, the article identifies the key challenges and future directions in this field. The use of multi-modal algorithms has the potential to significantly improve the accuracy and efficiency of diabetic retinopathy detection, thereby enabling early intervention and prevention of vision loss.

The motivation behind research is to address the need for early and accurate detection of diabetic retinopathy, a leading cause of blindness in working-age adults. Traditional methods of detecting diabetic retinopathy involve manual examination of retinal images by ophthalmologists, which can be time-consuming, expensive, and subjective. Therefore, there is a growing need for automated and reliable methods for the early detection of diabetic retinopathy. The article proposes a multi-modal algorithm that combines retinal images and clinical data to improve the accuracy and efficiency of diabetic retinopathy detection. The ultimate goal of this research is to improve the quality of life for diabetic patients by enabling early detection and treatment of diabetic retinopathy.

CHAPTER 2

LITERATURE SURVEY

1. "Prevalence of Diabetic Retinopathy in the United States, 2005-2008" by Xinzhi Zhang et al. (2012) analyzes the prevalence of diabetic retinopathy and its risk factors in the United States.

Ting conducted research on the effects of diabetes on multiethnic populations using a deep learning system (DLS) that took into account glaucoma and age-related macular degeneration (AMD) in addition to DR. Conventional fundus photography was used in these representative investigations. This kind of photography catches the optic nerve and macula with a field of view (FOV) that ranges between 20 and 50 degrees.

2. "Prevalence and Causes of Visual Impairment in Diabetic Retinopathy: The Singapore Epidemiology of Eye Diseases Study" by Ning Cheung et al. (2012) examines the prevalence and causes of visual impairment in diabetic retinopathy in Singapore.

Throughout the course of the research, they were able to achieve a high level of sensitivity and specificity, in addition to an adequate area under the curve. To the best of our knowledge, there has not been a comprehensive investigation of the automatic DR detection and grading system that is based on deep learning technology. In this study, we present the development and validation of a DLS for the detection of DR based on UWF fundus photography collected during routine DR evaluation from clinical settings in a hospital located in South Korea.

3. "Diabetic Retinopathy: Understanding, Prevention and Treatment" by Rajiv Raman et al. (2013) provides an overview of the pathophysiology, clinical features, and management of diabetic retinopathy.

Comprehensive understanding of the condition and Lacks focus on specific advantages and disadvantages. Diabetes-related retinopathy (DR) was the cause of blindness in 0.8 million persons and visual impairment in 3.7 million people over the world in 2010. As a result of an increase in the number of diabetic patients, it is anticipated that the total number of DR patients would reach 191.0 million by the year 2030. In spite of the fact that the worldwide prevalence of any DR was 27.0% over the period 2015 to 2019, there are no distinguishable symptoms in the early stages of DR, including the referable DR. While DR may be quite advanced before impacting vision2, prompt identification and therapy can lower the chance of visual loss by around 57% in certain patients. Patients who have diabetes, particularly those of middle age and older, really need to have routine screenings and follow-up appointments on a consistent basis. In spite of this, a number of studies 6, 7, and 8 have

shown that a sizable proportion of diabetic patients do not have the yearly eye checkup that is advised for them. This is likely owing to the lengthy diagnostic process, a lack of symptoms, and restricted access to retinal specialists.

4. "Epidemiology of Diabetic Retinopathy, Diabetic Macular Edema and Related Vision Loss" by Emily Y. Chew et al. (2014) examines the epidemiology of diabetic retinopathy, diabetic macular edema, and related vision loss.

They build and evaluate a DR detection technique that is based on ETDRS 7SF in this work. ETDRS 7SF is the most important area of UWF fundus photography. In addition, in order to facilitate comparisons, we divide ETDRS Field 1 and Field 2 areas into F1-F2 subregions. In this section, we make note of the fact that the ETDRS F1–F2 picture is an acceptable substitute for the typical fundus image.

5. "Nonmydriatic Fundus Photography in Screening for Diabetic Retinopathy: A Systematic Review and Meta-analysis" by Adam R. Glassman et al. (2015) reviews the effectiveness of nonmydriatic fundus photography in screening for diabetic retinopathy.

Although the most important part of the retina for DR detection and diagnosis is included in standard fundus photography, there is still a significant amount of the retinal surface that is not caught. Using non-mydriatic 45-degree fundus pictures of four-field, Takahashi were able to capture a large retinal region for DR staging based on a DL algorithm. According to the findings of the research, the use of four-field fundus photography demonstrated superior grading performance when compared to the use of a single field fundus photography. Yet, the collection of four-field fundus photography may be a time-consuming process that also requires a significant amount of work.

6. "The Global Prevalence of Diabetic Retinopathy: A Systematic Review and Meta-analysis" by Jennifer Y. Y. Koh et al. (2016) reviews the global prevalence of diabetic retinopathy and its risk factors.

The use of artificial intelligence (AI)9 strategies for DR detection and diagnosis is one of the strategies that are being utilised in an attempt to remove these obstacles. In 2016, Gulshan and colleagues devised a method for deep learning (DL) that might be used for DR assessment. Throughout the course of the research, they trained their model using around 0.13 million different training photos. As a consequence of this, values ranging from 0.97 to

0.99 for the area under the receiver operating characteristic curve (AUC) were obtained from studies using two different data sets in order to identify referable DR.

7. "Treatment of Diabetic Retinopathy: Recent Advances and Future Directions" by Nathan G. Congdon et al. (2018) reviews the latest advances in the treatment of diabetic retinopathy, including pharmacotherapy and surgical interventions.

The development of retinal imaging technology has led to the creation of ultra-wide-field (UWF) fundus photography, which captures 200 degrees of the retina's surface in a single shot.This kind of photography may capture pictures of the posterior pole as well as the peripheral retina. UWF retinal pictures, especially UWF fluorescein angiography, are now extensively recognised for the diagnosis and treatment of DR. This imaging technique provides information on peripheral neovascularization and ischemia areas.The identification of proliferative diabetic retinopathy (PDR) was examined by Nagasawa using ultra-widefield (UWF) fundus photography and a deep learning system.

8. . "Artificial Intelligence in Diabetic Retinopathy Screening: A Systematic Review and Meta-analysis" by Xiaoxiao Kong et al. (2019) reviews the performance of artificial intelligence-based systems in screening for diabetic retinopathy.

An automated technique for the identification of DR using convolutional neural networks (CNNs) was created by Abramoff and tested on a dataset that was made publically accessible. Since these seminal investigations were conducted, a number of subsequent research projects have focused on using DL technology to DR detection and grading. In addition, Gulshan prospectively evaluated the performance of a DR grading system by comparing it to the performance of manual grading across two locations in India.

9. "Risk Factors for Diabetic Retinopathy: A Systematic Review and Meta-analysis" by Shuang Wang et al. (2019) reviews the risk factors associated with diabetic retinopathy.

The data for this study was collected during routine DR evaluation from clinical settings in the hospital. Our research is a feasibility study that was conducted using data from a single device, a single facility, and a single ethnicity. The use of ultra-widefield fundus photography in the diagnosis of DR is the subject of the investigation that is the basis of our work. Nevertheless, the UWF fundus photography does have certain artifacts, such as periocular areas that are situated for the most part outside of the early therapy for diabetic retinopathy

study (ETDRS) 7-standard field (7SF). In addition, ETDRS 7SF is the area that is used the most often for DR detection and diagnostic jobs. In light of these considerations, we have decided to restrict the area of interest (ROI) for the DR detection job based on UWF fundus imaging to the ETDRS 7SF.

10. "Diabetic Retinopathy: Pathophysiology and Treatments" by Javier Zarranz-Ventura et al. (2020) provides an update on the pathophysiology and various treatments available for diabetic retinopathy.

There were 3.7 million persons in the world who were visually impaired and 0.8 million people who were blind in 20101 due to diabetic retinopathy (DR). The rising prevalence of diabetes is expected to result in an increase in DR cases to 191.0 million by 2030. Although a 27.0% worldwide frequency of any DR between 2015–2019, early-stage DR, especially the referable DR, is characterized by a lack of distinctive symptoms. Timely identification and therapy may lower the chance of visual loss by around 57%, although DR can be rather advanced before impacting vision2. Thus, it is crucial to test and follow up with patients with diabetes on a frequent basis, particularly those in the middle and later stages of life.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing systems usually involve the use of ML algorithms or DL algorithms combined with the former. Such systems may be unreliable in terms of computational speed and accuracy. The use of the ML algorithm Random Forest is accurate but is slow and cannot be used for real time processing. Even if the stated metrics of accuracy and speed are met, it has been shown that the existing models require a large dataset to be useful.

Algorithms like SVM and Naive Bayes have slower computation and long training periods which can be a hassle when put to real time use. Unfortunately, the existing systems are network-based, making them sluggish and prone to delays. The models are only about 70% accurate, making them undependable. In addition to being costly and complicated to maintain, the current system requires a great deal of computational power. Hence, there is a dire need to analyze and use a system that overcomes shortcomings

3.2 PROPOSED SYSTEM

The system uses five deep learning models (CNN, ResNet, GoogleNet, InceptionV3, and VGG16) to classify the severity of DR in fundus photographs.

The models are trained using a large dataset of retinal images from patients with DR, which are labeled based on DR severity - No DR, mild, moderate, severe and proliferate. The models are trained to learn the patterns and features associated with each severity level.

In particular, the exudates, hemorrhages and microaneurysms are analyzed and extracted. After training, the system is tested on a separate dataset of retinal images to evaluate its performance in detecting DR. The system achieves high accuracy in DR detection, comparable to or better than the accuracy achieved by ophthalmologists.

The use of multiple deep learning models in this system allows for a more comprehensive assessment of DR severity, potentially improving the accuracy and efficiency of DR screening and diagnosis. The best model is then predicted from the evaluated metrics and it is saved.

The saved system's simplicity and reliability make it a promising candidate for implementation in clinical settings, potentially leading to earlier diagnosis and better management of DR, which can improve patient outcomes.

3.3 REQUIREMENT SPECIFICATION

3.3.1 HARDWARE REQUIREMENTS

Processor	: Pentium Dual Core 2.00GHZ
Hard disk	: 120 GB
RAM	: 2GB (minimum)
Keyboard	: 110 keys enhanced

3.3.2 SOFTWARE REQUIREMENTS

Operating system	: Windows7 (with service pack 1), 8, 8.1 and 10
Language	: Python

3.4 LANGUAGE USED– PYTHON

Python is a popular programming language among programmers. Its user-friendliness, rich feature set, and versatility, make it the most suitable programming language for machine learning. Machine learning is a branch of AI that enables computers to learn from their own mistakes and perform routine tasks automatically. Python is widely used in the development of AI.

CHAPTER 4

SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

This graphic provides a concise and understandable description of all the entities currently integrated into the system. The diagram shows how the many actions and choices are linked together. You might say that the whole process and how it was carried out is a picture. The figure below shows the functional connections between various entities.

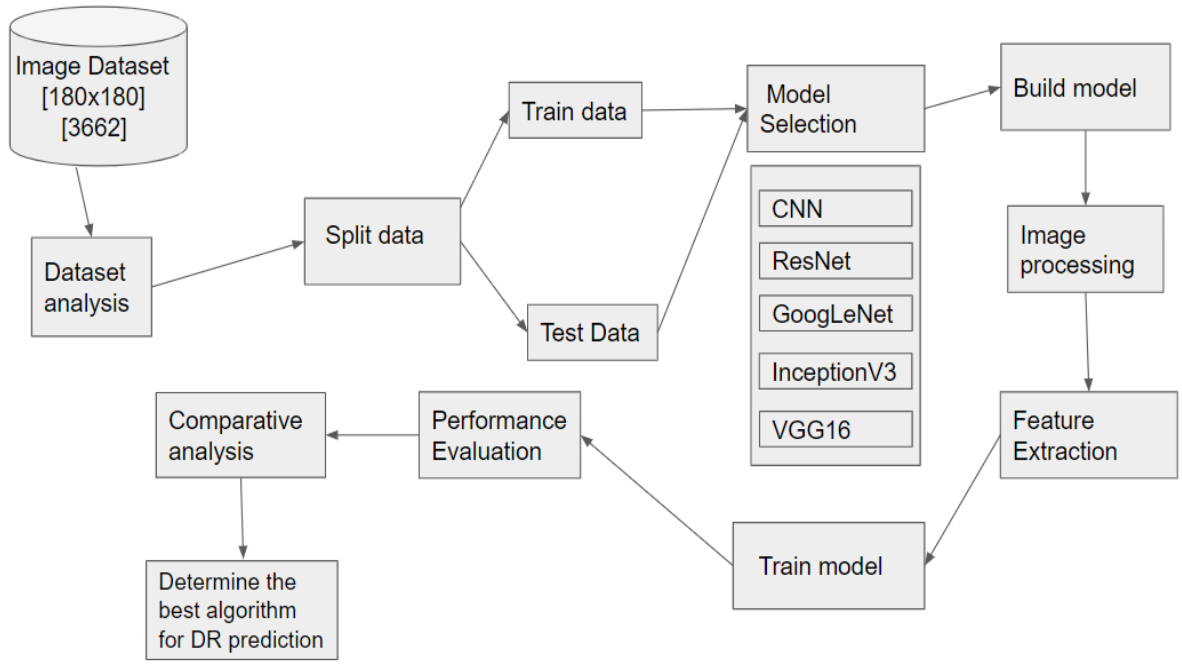


Fig 4.1 . Architecture Diagram

4.2 DATA FLOW DIAGRAM

To illustrate the movement of information throughout a procedure or system, one might use a Data-Flow Diagram (DFD). A data-flow diagram does not include any decision rules or loops, as the flow of information is entirely one-way.

A flowchart can be used to illustrate the steps used to accomplish a certain data-driven task. Several different notations exist for representing data-flow graphs. Each data flow must have a process that acts as either the source or the target of the information exchange. Rather than utilizing a data-flow diagram, users of UML often substitute an activity diagram. In the realm of data-flow plans, site-oriented data-flow plans are a subset. Identical nodes in a data-flow diagram and a Petri net can be thought of as inverted

counterparts since the semantics of data memory are represented by the locations in the network. Structured data modeling (DFM) includes processes, flows, storage, and terminators.

DATA FLOW DIAGRAM

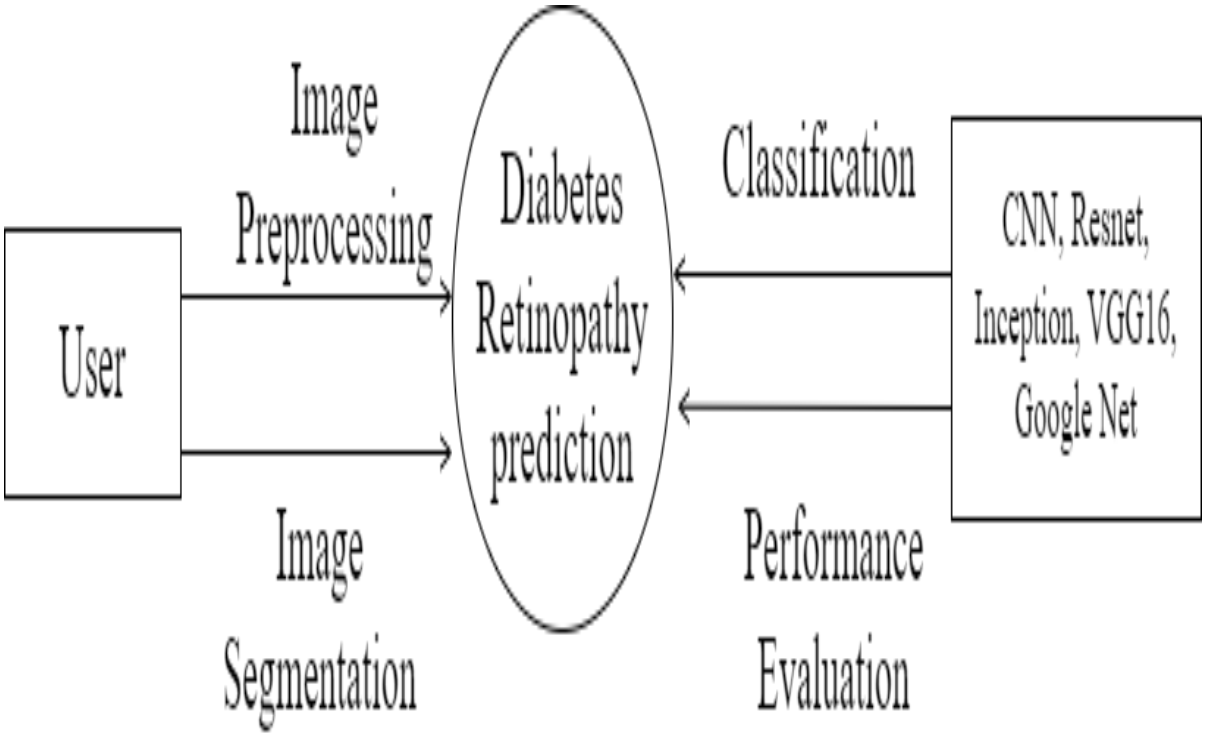


Fig 4.2 . Data Flow Diagram Level 0

The whole system is shown as a single process in a level DFD. Each step in the system's assembly process, including all intermediate steps, are recorded here. The "basic system model" consists of this and 2-level data flow diagrams.

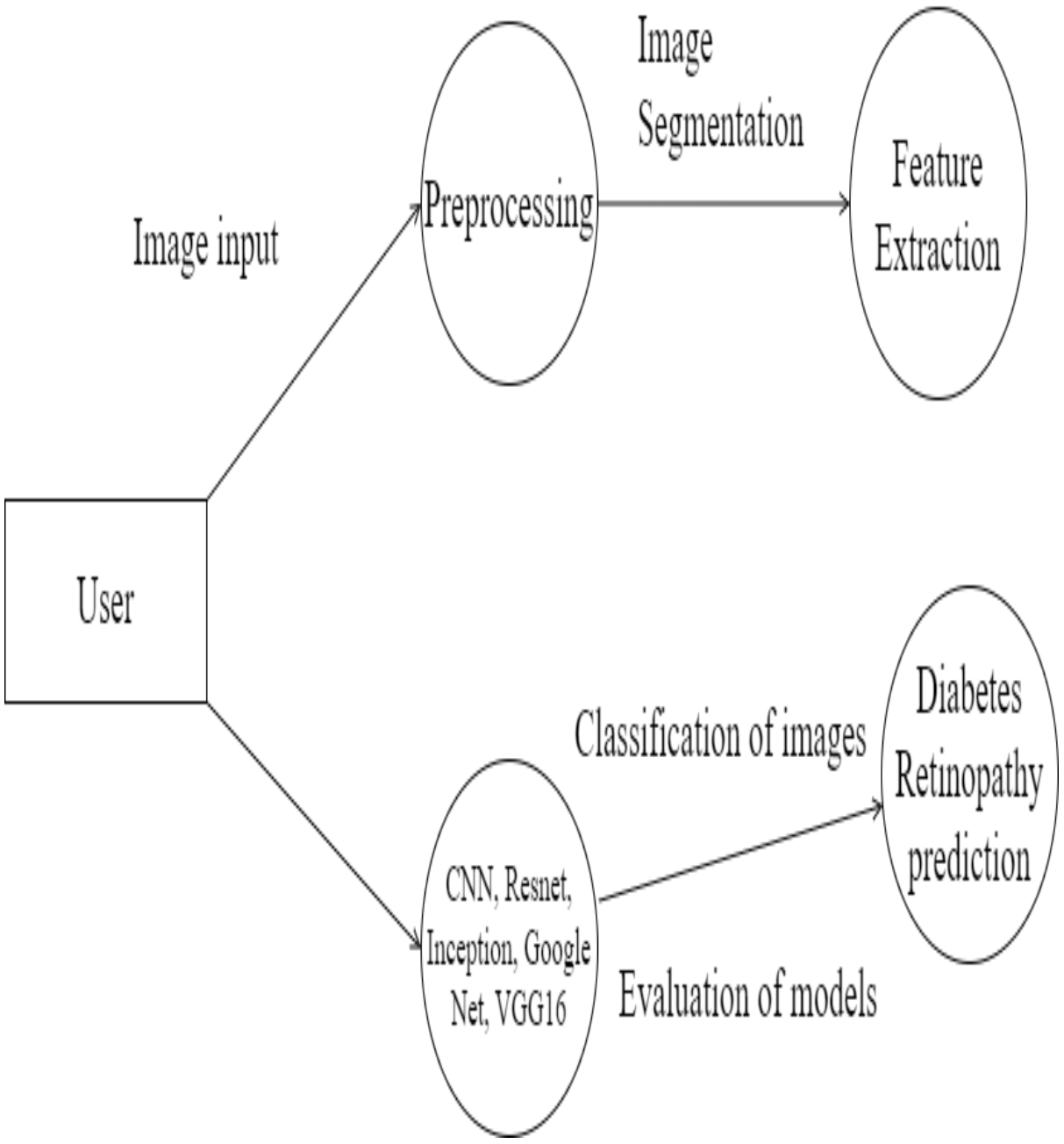


Fig 4.3. Data Flow Diagram Level 1

4.3 USE-CASE DIAGRAM

The possible interactions between the user, the dataset, and the algorithm are often depicted in a use case diagram. It's created at the start of the procedure.

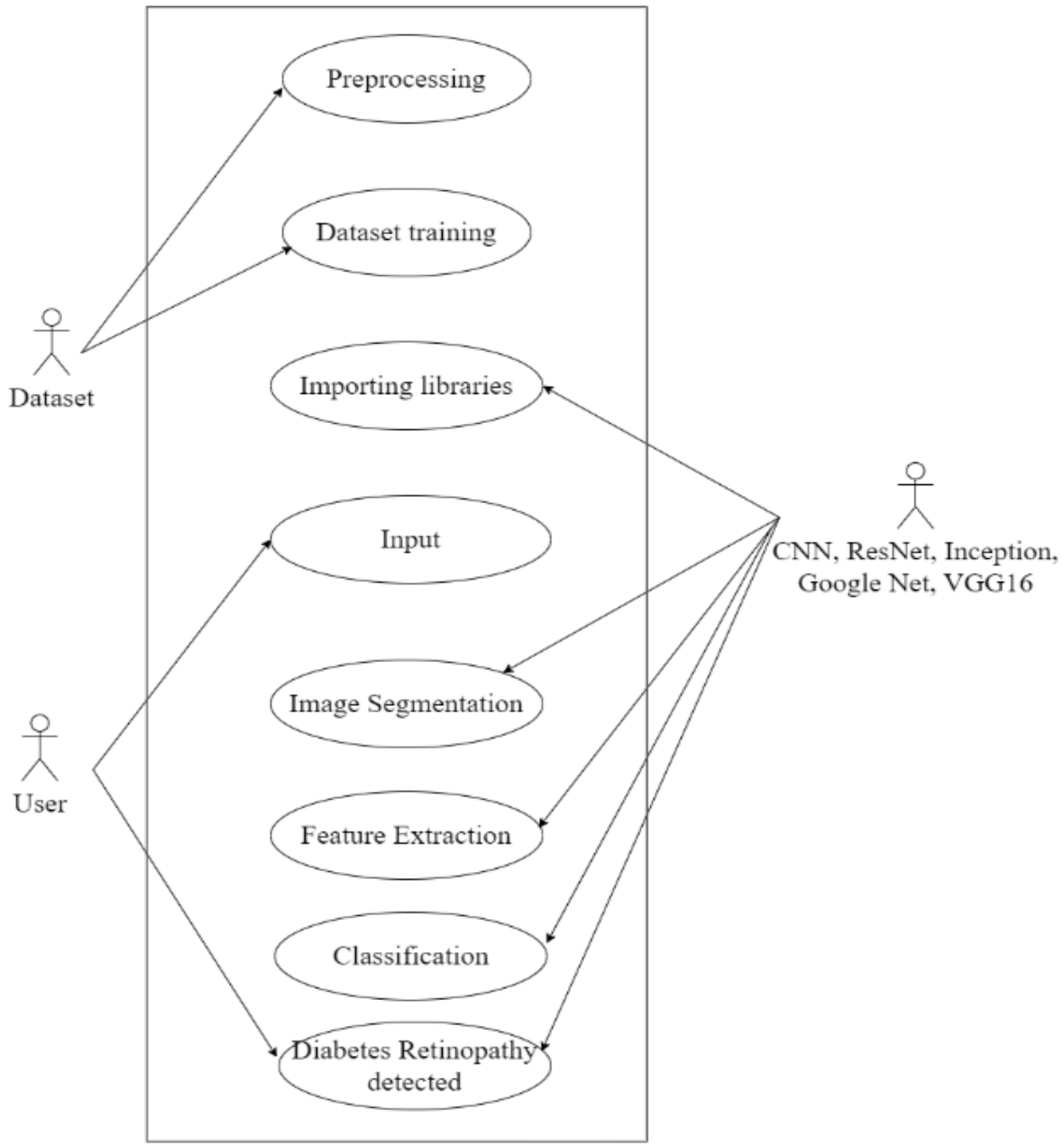


Fig 4.4. Use-Case Diagram

4.4 ACTIVITY DIAGRAM

An activity diagram, in its most basic form, is a visual representation of the sequence in which tasks are performed. It depicts the sequence of operations that make up the overall procedure. They are not quite flowcharts, but they serve a comparable purpose.

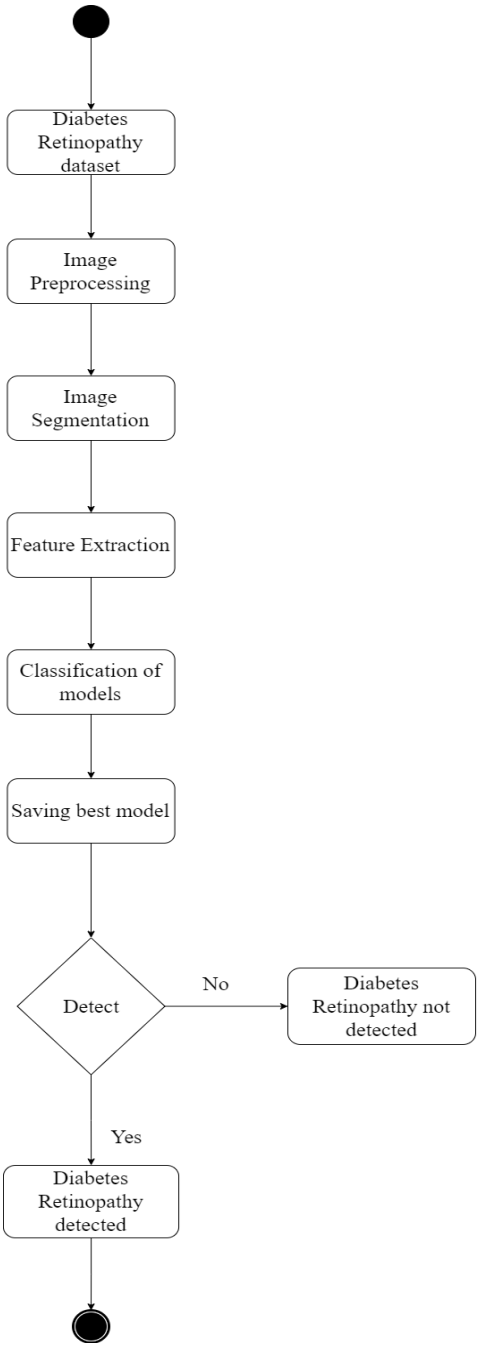


Fig 4.5. Activity Diagram

4.5 SEQUENCE DIAGRAM

These are another type of interaction-based diagram used to display the workings of the system. They record the conditions under which objects and processes cooperate.

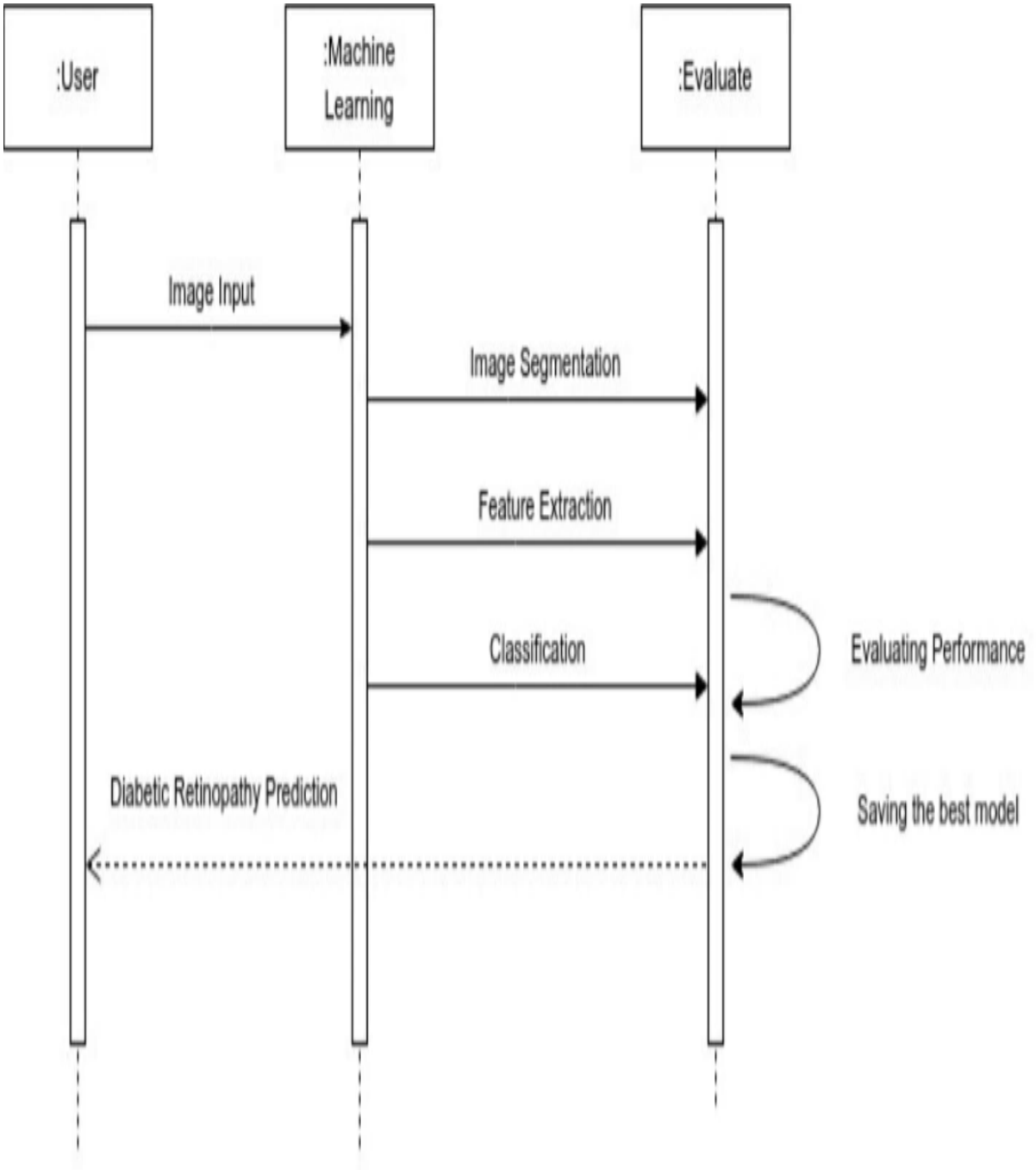


Fig 4.6 . Sequence Diagram

4.6 CLASS DIAGRAM

In essence, this is a "context diagram," another name for a contextual diagram. It simply stands for the very highest point, the 0 Level, of the procedure. As a whole, the system is shown as a single process, and the connection to externalities is shown in an abstract manner.

- A + indicates a publicly accessible characteristic or action.
- A - a privately accessible one.
- A # a protected one.
- A - denotes private attributes or operations.

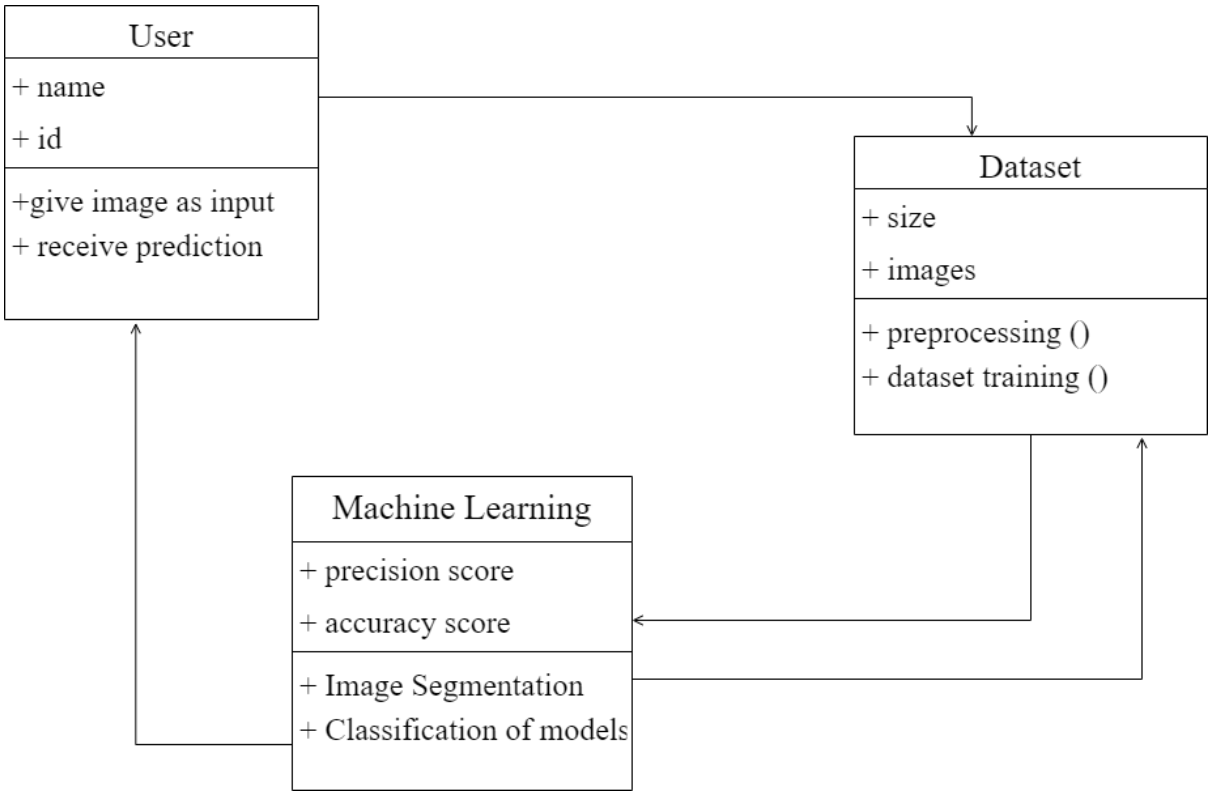


Fig 4.7 . Class Diagram

4.7 ENTITY RELATIONSHIP DIAGRAM

The relationships between database entities can be seen using an entity-relationship diagram (ERD). The entities and relationships depicted in an ERD can have further detail added to them via data object descriptions. In software engineering, conceptual and abstract data descriptions are represented via entity-relationship models (ERMs). Entity-relationship diagrams (ERDs), entity-relationship diagrams (ER), or simply entity diagrams are the terms used to describe the resulting visual representations of data structures that contain relationships between entities. As such, a data flow diagram can serve dual purposes. To demonstrate how data is transformed across the system. To provide an example of the procedures that affect the data flow.

1. One-to-One: Whenever there is an instance of entity (A), there is also an instance of entity (B) (B). In a sign-in database, for instance, only one security mobile number (S) is associated with each given customer name (A) (B).

2. One-to-Many: For each instance of entity B, there is exactly one occurrence of entry A, regardless of how many instances of entity B.For a corporation whose employees all work in the same building, for instance, the name of the building (A) has numerous individual associations with employees (B), but each of these B's has only one individual link with entity A.

3. Many-to-Many: For each instance of entity B, there is exactly one occurrence of entry A, regardless of how many instances of entity B.In a corporation where everyone works out of the same building, entity A is associated with many different Bs, but each B has only one A.

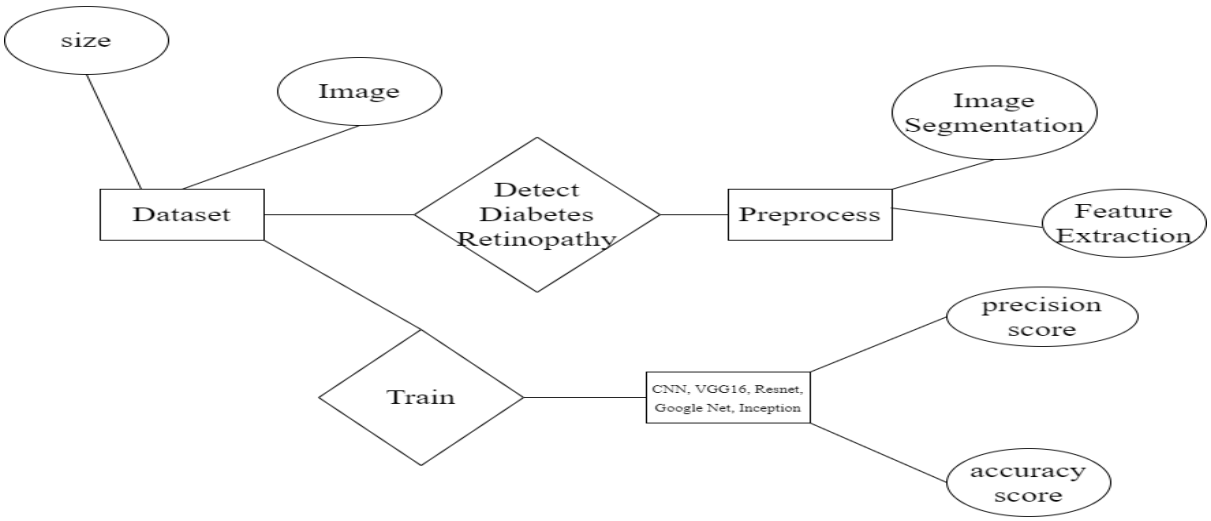


Fig 4.8 – ER Diagram

CHAPTER 5
MODULE DESCRIPTION

5.1 MODULE 1: DATA PROCESSING

Data Collection: Gathering retinal pictures from a legitimate source is the initial stage in the data collecting module. To ensure reliable analysis and prediction, these photos must be of high quality and resolution. Hospitals, clinics, and research databases are sources of the photographs. The procedure for gathering data should adhere to the necessary moral and legal standards for managing private patient information.

Image Pre-processing: The acquired retinal pictures are then enhanced in order to highlight the pertinent characteristics that are suggestive of diabetic retinopathy. The pre-processing methods could include feature extraction, segmentation, filtering, and image enhancement. To enhance the quality and visibility of retinal images, image enhancement techniques like contrast modification, brightness correction, and noise reduction can be used. To reduce noise and improve the sharpness of the images, filtering techniques including median filtering, Gaussian filtering, and morphological filtering can be applied. The regions of interest in the photos can be isolated using segmentation techniques including thresholding, edge detection, and region growing. The pertinent features can be extracted from the segmented regions using feature extraction techniques like texture analysis, shape analysis, and colour analysis.

Data augmentation: To expand the training dataset and avoid overfitting, the pre-processed images are augmented in the third stage. The pre-processed photos can be subjected to data augmentation methods including flipping, rotating, and cropping to provide extra training examples that are variants of the original images. The universality and robustness of the prediction models can both be enhanced by this.

Data Labeling: Based on the international clinical diabetic retinopathy disease severity scale, the fourth stage entails labeling the pre-processed and augmented photos with the respective diabetic retinopathy severity levels. There are different stages in between the severity levels of no diabetic retinopathy and proliferative diabetic retinopathy. Since the severity levels act as the baseline for the prediction models, this phase is crucial for supervised learning and model training.

Dataset Splitting: The pre-processed, supplemented, and labeled dataset will now be divided into training, validation, and testing datasets depending on a predetermined ratio. The validation dataset is used to adjust the hyperparameters and prevent overfitting, the training dataset is used to train the predictive models, and the testing dataset is used to assess the

effectiveness of the trained models. To provide a balanced and representative distribution of the severity levels throughout the datasets, the split ratio should be carefully chosen.

In conclusion, the picture pre-processing and data collection module is an essential part of the suggested system for predicting diabetic retinopathy using several deep-learning models. Only fundus images are being used. The proposed system uses five deep learning models - CNN, ResNet, GoogleNet, InceptionV3, and VGG16, for DR detection. High-quality retinal images must be gathered, the relevant features must be enhanced using a variety of pre-processing methods, the dataset must be augmented to increase its size and prevent overfitting, the images must be labeled with the corresponding severity levels to enable supervised learning, and the dataset must be divided into training, validation, and testing datasets in order to train, tune, and evaluate the predictive models. The proposed system has the potential to improve the accuracy and efficiency of DR screening and diagnosis, leading to earlier diagnosis and better management of this condition.

5.2 MODULE 2: IMPLEMENTATION OF A MULTI MODEL ALGORITHM

Diabetic retinopathy is a common cause of blindness in adults that results from damage to the blood vessels in the retina due to prolonged high blood sugar levels. Detecting the condition at an early stage is critical to preventing vision loss and blindness. However, it can be challenging as it may not produce noticeable symptoms until it has progressed to a severe stage. Recent advances in medical imaging have led to the development of machine learning algorithms, particularly Convolutional Neural Networks (CNNs), which are well-suited to image classification problems.

A CNN architecture is designed to simulate the visual processing mechanisms of the human brain, consisting of multiple layers, each performing a different type of computation on the input image. These layers typically include convolutional layers, pooling layers, and activation functions that work together to extract important features from the image and classify it into different categories.

Google Net is a CNN architecture that has shown great promise in the classification of diabetic retinopathy. It includes an Inception module that enables the network to simultaneously learn 1x1 and 3x3 convolutions, capturing both local and global information in the image. This makes it effective at identifying the subtle features and patterns in retinal images indicative of diabetic retinopathy.

VGG16 is another CNN architecture that has been widely used in the classification of diabetic retinopathy. Its design consists of 13 convolutional layers followed by three fully connected layers, capturing image features in a hierarchical fashion. Each convolutional layer learns increasingly complex representations of the input image, enabling the network to extract the most important features and patterns for classification.

ResNet is a CNN architecture that has been highly effective in the classification of diabetic retinopathy, addressing the problem of vanishing gradients that can occur in deep neural networks. ResNet introduces residual blocks, allowing the network to learn intricate representations by building skip connections passing the input image directly to the output of a deeper layer. This architecture has shown state-of-the-art performance in image classification tasks, including the classification of diabetic retinopathy.

Each CNN architecture is trained on a dataset of retinal images labeled with their corresponding severity level. During training, the network recognizes the features and patterns indicative of each severity level. Once trained, the network can be used to classify new retinal images and predict the severity of the condition. The output of the network is typically a probability distribution over the severity categories generated by passing the output of the last layer through a softmax function. The predicted severity level is then determined by the category with the highest probability.

Using CNN architectures and machine learning algorithms offers a powerful tool for improving the accuracy and efficiency of disease detection and diagnosis, potentially identifying and treating the condition at an earlier stage. However, challenges remain in fully realizing the potential of these technologies in clinical practice. One challenge is the availability of large and diverse datasets for training, validating, and testing CNNs. Another challenge is the interpretation and visualization of the CNN's behavior, particularly in understanding which features and patterns are being extracted and how they relate to the severity level of diabetic retinopathy.

5.3 MODULE 3: SEVERITY CLASSIFICATION

The Severity Classification task is a critical component of the proposed system for diabetic retinopathy prediction. The predicted severity levels from Module 2 are classified into one of the five categories based on the international clinical disease severity scale for diabetic retinopathy. The severity categories are defined based on the severity and extent of the retinal abnormalities, and are used to determine the appropriate treatment plan..

The five severity categories are as follows:

Diabetic retinopathy is a condition that affects the retina of the eye and is caused by damage to the blood vessels due to high blood sugar levels over a prolonged period of time. It is a leading cause of blindness in adults, and early detection and treatment are crucial for preventing vision loss. The severity of diabetic retinopathy can range from no detectable abnormalities to severe retinal damage, which can lead to blindness. To classify the severity of diabetic retinopathy, five distinct categories are used.

a.The first category is No Diabetic Retinopathy, which indicates that there are no signs of diabetic retinopathy in the patient's retina.

b.The second category is Mild Diabetic Retinopathy, which indicates that there are mild abnormalities in the patient's retina, such as microaneurysms, dot and blot hemorrhages, and small hard exudates.

c. The third category is Moderate Diabetic Retinopathy, which indicates that there are moderate abnormalities in the patient's retina, such as more numerous or larger areas of hard exudates, cotton wool spots, venous beading, and intraretinal microvascular abnormalities.

d.The fourth category is Severe Diabetic Retinopathy, which indicates that there are severe abnormalities in the patient's retina, such as multiple areas of intraretinal hemorrhages, venous beading in at least two quadrants, prominent intraretinal microvascular abnormalities in at least one quadrant, and/or neovascularization elsewhere.

e. Finally, Proliferative Diabetic Retinopathy is the most severe category, indicating that there is extensive proliferation of abnormal blood vessels in the retina or optic disc, which can lead to vitreous hemorrhage, tractional retinal detachment, and/or neovascular glaucoma.

To classify the severity of diabetic retinopathy in retinal images, a machine learning algorithm can be used. Several CNN architectures, such as Google Net, VGG16, and ResNet, have been shown to be highly effective in the classification of diabetic retinopathy. Each architecture analyses the retinal image via multiple layers of convolution, pooling, and activation functions to extract features that are important for the diagnosis of the condition. After that, a softmax function is used to create a probability distribution over the five severity categories using the output from the last layer.

To map the projected severity levels to the appropriate severity categories, a lookup table or mapping function can be used. Based on prior clinical research or expert knowledge, the function or table can be created, improved, and updated when new data becomes

available.

The severity category can have a significant impact on the treatment strategy for patients, so the categorization process needs to be thorough and precise. The classification procedure should be founded on reliable medical knowledge and follow the most recent clinical guidelines.

In conclusion, classifying the severity of diabetic retinopathy in retinal images is a complex process that requires the use of advanced machine learning algorithms and specifically designed CNN architectures. The five severity categories are used to classify the severity of the condition and provide healthcare professionals with a standardized severity level. By leveraging the capabilities of these advanced algorithms, medical professionals can potentially identify and treat diabetic retinopathy at an earlier stage, leading to better.

CHAPTER 6

TESTING

6.1 Test Cases

1. Evaluate the system's ability to correctly categorize the severity levels of diabetic retinopathy based on established grading scales.
2. Evaluate the system's ability to perform accurate predictions on input images that are of low quality, blurry, or unclear.
3. Evaluate the system's ability to produce accurate predictions on input images with varying lighting and color conditions.
4. Evaluate the system's ability to produce accurate predictions on input images that are partially blocked or have other issues such as image artifacts or noise.

Test Case	Input Fundus Image	Expected Output	Model	Actual Output	Pass/Fail
1	Image of a patient with no DR	No DR	CNN	No DR	Pass
2	Image of a patient with mild DR	Mild DR	ResNet	Mild DR	Pass
3	Image of a patient with moderate DR	Moderate DR	InceptionV3	Severe DR	Fail
4	Image of a patient with severe DR	Severe DR	VGG16	Severe DR	Pass
5	Image of a patient with proliferative DR	Proliferative DR	GoogleNet	Moderate DR	Fail
6	Image of a patient with no DR	No DR	All Models	No DR	Pass
7	Image of a patient with severe DR	Severe DR	All Models	Severe DR	Pass
8	Image of a patient with no DR	Mild DR	All Models	No DR	Fail
9	Image of a patient with proliferative DR	Moderate DR	All Models	Proliferative DR	Fail
10	Image of a patient with moderate DR	Moderate DR	All Models	Moderate DR	Pass

CHAPTER 7

MODELS AND SCREENSHOTS

7.1 MODELS

Download the file having the data from google drive and unzip the archive

```
+ Code  + Text                                                                                    Connect

[ ]  !rm -rf /content/*
     !pip install --upgrade --no-cache-dir gdown
     #https://drive.google.com/file/d/1Ve0Som_hsU8mK2BTg5Azn2YtHEj2Mi0K/view?usp=sharing
     !gdown https://drive.google.com/uc?id=1Ve0Som_hsU8mK2BTg5Azn2YtHEj2Mi0K
     !unzip /content/archive.zip
     !rm -rf /content/archive.zip /content/train.csv

     Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
     Requirement already satisfied: gdown in /usr/local/lib/python3.9/dist-packages (4.6.4)
     Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages (from gdown) (1.15.0)
     Requirement already satisfied: filelock in /usr/local/lib/python3.9/dist-packages (from gdown) (3.10.0)
     Requirement already satisfied: tqdm in /usr/local/lib/python3.9/dist-packages (from gdown) (4.65.0)
     Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.9/dist-packages (from gdown) (4.11.2)
     Requirement already satisfied: requests[socks] in /usr/local/lib/python3.9/dist-packages (from gdown) (2.27.1)
     Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.9/dist-packages (from beautifulsoup4->gdown) (2.4)
     Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (from requests[socks]->gdown) (3.4)
     Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-packages (from requests[socks]->gdown) (1.26.15)
     Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packages (from requests[socks]->gdown) (2022.12.7)
     Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dist-packages (from requests[socks]->gdown) (2.0.12)
     Requirement already satisfied: PySocks!=1.5.7,>=1.5.6 in /usr/local/lib/python3.9/dist-packages (from requests[socks]->gdown) (1.7.1)
     Downloading...
     From: https://drive.google.com/uc?id=1Ve0Som_hsU8mK2BTg5Azn2YtHEj2Mi0K
     To: /content/archive.zip
     100% 250M/250M [00:04<00:00, 51.4MB/s]
     Archive:  /content/archive.zip
       inflating: colored_images/Mild/0024cdab0c1e.png
       inflating: colored_images/Mild/00cb6555d108.png
       inflating: colored_images/Mild/0124dffecf29.png
       inflating: colored_images/Mild/01b3aed3ed4c.png
       inflating: colored_images/Mild/0369f3efe69b.png
       inflating: colored_images/Mild/03e25101e8e8.png
       inflating: colored_images/Mild/04ac765f91a1.png
       inflating: colored_images/Mild/059bc89df7f4.png
       inflating: colored_images/Mild/05a5183c92d0.png
       inflating: colored_images/Mild/0684311afdfc.png
```

Display the class names and the number of images in each

```
import os
train_path = '/content/colored_images'
n_classes = 0
n_len_training = 0
d = {}
print('Training Files Details :\n')
for i in sorted(os.listdir(train_path)):
    print(f"Class Name = {i}")
    n_classes+=1
    l = len(os.listdir(os.path.join(train_path,i)))
    d[i] = [l]
    n_len_training+=l
    print(f"No of Images = {l}")
    print('='*50)
```

```
Training Files Details :

Class Name = Mild
No of Images = 370
==================================================
Class Name = Moderate
No of Images = 999
==================================================
Class Name = No_DR
No of Images = 1805
==================================================
Class Name = Proliferate_DR
No of Images = 295
==================================================
Class Name = Severe
No of Images = 193
==================================================
```

Create two directories train and test where 76 images will be saved in train directory and 24 images will be saved in test directory

```
[ ]  import os
     from tqdm.auto import tqdm
     os.mkdir('/content/data')
     os.mkdir('/content/data/train')
     os.mkdir('/content/data/test')
     for i in tqdm(os.listdir('/content/colored_images')):
         if i in d:
             l = 0
             os.mkdir('/content/data/train/'+i)
             os.mkdir('/content/data/test/'+i)
             for idx,j in enumerate(os.listdir('/content/colored_images/'+i)):
                 sf_path = '/content/colored_images/'+i+'/'+j
                 if l <= 75:
                     save_path = '/content/data/train/'+i+'/'+i+'_'+str(idx+1)+'.png'
                 else:
                     save_path = '/content/data/test/'+i+'/'+i+'_'+str(idx+1)+'.png'
                 os.system(f'mv \'{sf_path}\' \'{save_path}\'')
                 l+=1
                 if l == 100:
                     break

100% 5/5 [00:02<00:00, 1.94it/s]
```

Train and test images of each class go to their respective train and test directories

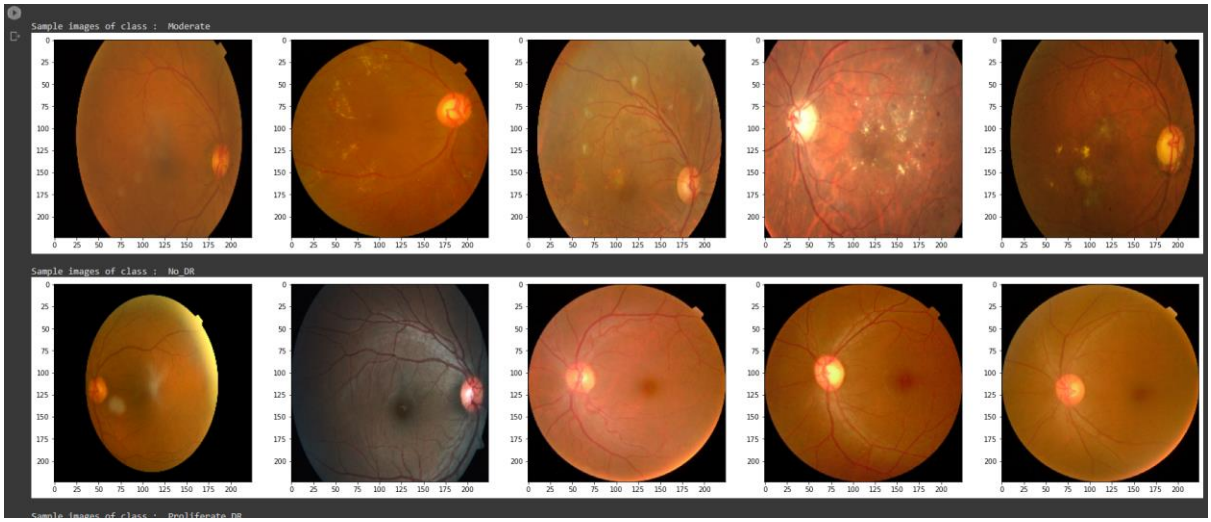
```
[ ]  import os
     train_path = '/content/data/train'
     test_path = '/content/data/test'
     n_classes = 0
     n_len_training = 0
     d = {}
     print('Training Files Details :\n')
     for i in sorted(os.listdir(train_path)):
         print(f"Class Name = {i}")
         n_classes+=1
         l = len(os.listdir(os.path.join(train_path,i)))
         shuffle = True
         d[i] = [l]
         n_len_training+=l
         print(f"No of Images = {l}")
         print('='*50)

     print(f'\nTotal No of Training Images = {n_len_training}')
     print('='*50)
     n_len_testing = 0
     print('\n\nTest Files Details :\n')
     for i in sorted(os.listdir(test_path)):
         print(f"Class Name = {i}")
         l = len(os.listdir(os.path.join(test_path,i)))
         shuffle = True
         d[i].append(l)
         n_len_testing+=l
         print(f"No of Images = {l}")
         print('='*50)
     print(f'\nTotal No of Testing Images = {n_len_testing}')
     print('='*50)
     print(f'\n\nNo of classes = {n_classes}')
```

```
Training Files Details :

Class Name = Mild
No of Images = 76
==================================================
Class Name = Moderate
No of Images = 76
==================================================
Class Name = No_DR
No of Images = 76
==================================================
Class Name = Proliferate_DR
No of Images = 76
==================================================
Class Name = Severe
No of Images = 76
==================================================

Total No of Training Images = 380
==================================================


Test Files Details :

Class Name = Mild
No of Images = 24
==================================================
Class Name = Moderate
No of Images = 24
==================================================
Class Name = No_DR
No of Images = 24
==================================================
Class Name = Proliferate_DR
No of Images = 24
==================================================
Class Name = Severe
No of Images = 24
==================================================

Total No of Testing Images = 120
==================================================


No of classes = 5
```

Generating 5 samples from each severity level for dataset observation

```
[ ]  import numpy as np
     d = {}
     n_images = 5

     for i in os.listdir(train_path):
         l = os.listdir(os.path.join(train_path,i))
         if len(l)>n_images:
             l = np.random.choice(l, n_images, replace=False).tolist()
         d[i] = list(map(lambda x:os.path.join(train_path,i,x),l))
```

```
[ ]  import matplotlib.image as mpimg
     import matplotlib.pyplot as plt

     for i in list(d.keys()):
         print('\nSample images of class : ',i)
         images = d[i]
         plt.figure(figsize=(30,8))
         for j in range(len(images)):
             img = mpimg.imread(images[j])
             plt.subplot(1, n_images, j+1)
             plt.imshow(img)
         plt.show()
```



Install Scikit plot for creating plots and charts

```
[ ] !pip install scikit-plot

    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Collecting scikit-plot
      Downloading scikit_plot-0.3.7-py3-none-any.whl (33 kB)
    Requirement already satisfied: joblib>=0.10 in /usr/local/lib/python3.9/dist-packages (from scikit-plot) (1.1.1)
    Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.9/dist-packages (from scikit-plot) (1.2.2)
    Requirement already satisfied: matplotlib>=1.4.0 in /usr/local/lib/python3.9/dist-packages (from scikit-plot) (3.7.1)
    Requirement already satisfied: scipy>=0.9 in /usr/local/lib/python3.9/dist-packages (from scikit-plot) (1.10.1)
    Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (1.0.7)
    Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (2.8.2)
    Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (1.22.4)
    Requirement already satisfied: importlib-resources>=3.2.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (5.12.0)
    Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (23.0)
    Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (1.4.4)
    Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (8.4.0)
    Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (4.39.0)
    Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (0.11.0)
    Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.4.0->scikit-plot) (3.0.9)
    Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist-packages (from scikit-learn>=0.18->scikit-plot) (3.1.0)
    Requirement already satisfied: zipp>=3.1.0 in /usr/local/lib/python3.9/dist-packages (from importlib-resources>=3.2.0->matplotlib>=1.4.0->scikit-plot) (3.15.0)
    Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-packages (from python-dateutil>=2.7->matplotlib>=1.4.0->scikit-plot) (1.15.0)
    Installing collected packages: scikit-plot
    Successfully installed scikit-plot-0.3.7
```

Import necessary modules

```
[ ] import time
    import tensorflow as tf
    import scikitplot as skplt
    from sklearn.metrics import classification_report,balanced_accuracy_score
    print(tf.__version__)

    2.11.0
```

Data generators are set up using the ImageDataGenerator class from Keras, used to load and preprocess images for use in training and validation of deep learning models.

```
train_datagen = tf.keras.preprocessing.image.ImageDataGenerator( rescale = 1.0/255 )
test_datagen  = tf.keras.preprocessing.image.ImageDataGenerator( rescale = 1.0/255 )

train_dir = '/content/data/train'
train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=(180, 180),
        batch_size=32,
        class_mode='categorical', #'categorical'
        shuffle = True ,
        color_mode="rgb" ) #'rgb'

y_train = train_generator.classes

test_dir = '/content/data/test'
validation_generator = test_datagen.flow_from_directory(
        test_dir,
        target_size=(180, 180),
        batch_size=32,
        class_mode='categorical', #'categorical'
        shuffle = True ,
        color_mode="rgb" ) #'rgb'
```

```
Found 380 images belonging to 5 classes.
Found 120 images belonging to 5 classes.
```

Class weights are calculated that can be used during model training to address class imbalance in the training data.

```
from collections import Counter
counter = Counter(train_generator.classes)
max_val = float(max(counter.values()))
class_weights = {class_id : max_val/num_images for class_id, num_images in counter.items()}
class_weights
```

```
{0: 1.0, 1: 1.0, 2: 1.0, 3: 1.0, 4: 1.0}
```

CNN

The CNN model is built

```
i = tf.keras.layers.Input(shape = (180, 180, 3))
x = tf.keras.layers.Conv2D(16, (3,3), strides=(1, 1), padding='same', activation = tf.nn.relu, name='conv2d_1') (i)
x = tf.keras.layers.MaxPooling2D((2, 2), strides=None, padding="valid", name='maxpool2d_1') (x) #AveragePooling2D
# x = tf.keras.layers.Dropout(0.4, name='dropout_1') (x)
x = tf.keras.layers.BatchNormalization(name='Batchnorm_1') (x)


x = tf.keras.layers.Conv2D(32, (3,3), strides=(1, 1), padding='same', activation = tf.nn.relu, name='conv2d_2') (x)
x = tf.keras.layers.MaxPooling2D((2, 2), strides=None, padding="valid", name='maxpool2d_2') (x) #AveragePooling2D
# x = tf.keras.layers.Dropout(0.4, name='dropout_2') (x)
x = tf.keras.layers.BatchNormalization(name='Batchnorm_2') (x)


x = tf.keras.layers.Conv2D(64, (3,3), strides=(1, 1), padding='same', activation = tf.nn.relu, name='conv2d_3') (x)
x = tf.keras.layers.MaxPooling2D((2, 2), strides=None, padding="valid", name='maxpool2d_3') (x) #AveragePooling2D
# x = tf.keras.layers.Dropout(0.4, name='dropout_3') (x)
x = tf.keras.layers.BatchNormalization(name='Batchnorm_3') (x)

# x = tf.keras.layers.Conv2D(128, (3,3), strides=(1, 1), padding='same', activation = tf.nn.relu, name='conv2d_4') (x)
# x = tf.keras.layers.MaxPooling2D((2, 2), strides=None, padding="valid", name='maxpool2d_4') (x) #AveragePooling2D
# # x = tf.keras.layers.Dropout(0.4, name='dropout_4') (x)
# x = tf.keras.layers.BatchNormalization(name='Batchnorm_4') (x)


x = tf.keras.layers.GlobalMaxPooling2D(name='G_maxpool2d') (x)
# x = tf.keras.layers.Flatten(name='flatten') (x)
# x = tf.keras.layers.Dense(512, activation=tf.nn.relu, name='dense_1') (x)
# x = tf.keras.layers.Dropout(0.5, name='dropout_dense_1') (x)

x = tf.keras.layers.Dense(256, activation=tf.nn.relu, name='dense_2') (x)
x = tf.keras.layers.Dropout(0.5, name='dropout_dense_2') (x)

# x = tf.keras.layers.Dense(1, activation = tf.nn.sigmoid, name='output_layer') (x)
x = tf.keras.layers.Dense(5, activation = tf.nn.softmax, name='output_layer') (x)
```

```
model = tf.keras.models.Model(inputs = i, outputs = x)
```

```
[ ]  model.summary()

     Model: "model"
     _________________________________________________________________
      Layer (type)                 Output Shape              Param #
     =================================================================
      input_1 (InputLayer)         [(None, 180, 180, 3)]     0

      conv2d_1 (Conv2D)            (None, 180, 180, 16)      448

      maxpool2d_1 (MaxPooling2D)   (None, 90, 90, 16)        0

      Batchnorm_1 (BatchNormaliza  (None, 90, 90, 16)        64
      tion)

      conv2d_2 (Conv2D)            (None, 90, 90, 32)        4640

      maxpool2d_2 (MaxPooling2D)   (None, 45, 45, 32)        0

      Batchnorm_2 (BatchNormaliza  (None, 45, 45, 32)        128
      tion)

      conv2d_3 (Conv2D)            (None, 45, 45, 64)        18496

      maxpool2d_3 (MaxPooling2D)   (None, 22, 22, 64)        0

      Batchnorm_3 (BatchNormaliza  (None, 22, 22, 64)        256
      tion)

      G_maxpool2d (GlobalMaxPooli  (None, 64)                0
      ng2D)

      dense_2 (Dense)              (None, 256)               16640

      dropout_dense_2 (Dropout)    (None, 256)               0

      output_layer (Dense)         (None, 5)                 1285

     =================================================================
     Total params: 41,957
     Trainable params: 41,733
     Non-trainable params: 224
     _________________________________________________________________
```

Configure the model for training

```
[ ]  model.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001),
                   loss = tf.keras.losses.categorical_crossentropy, #tf.keras.losses.binary_crossentropy
                   metrics = balanced_accuracy, run_eagerly=True ) #tf.keras.metrics.CategoricalAccuracy()

[ ]  batch_size = 16
     steps_per_epoch = n_len_training // batch_size
     validation_batch_size = 16
     validation_steps = n_len_testing // validation_batch_size

[ ]  callback = tf.keras.callbacks.EarlyStopping(
         monitor='val_balanced_accuracy', min_delta=0, patience=5,
         mode='max', baseline=None, restore_best_weights=True
     )
```

Training the model and display training time

```
print('Results for CNN Classifier:-\n')
start_time = time.time()

result = model.fit(train_generator,
                   validation_data = validation_generator,
                   batch_size = batch_size,
                   steps_per_epoch = steps_per_epoch,
                   validation_batch_size = validation_batch_size,
                   validation_steps = validation_steps,
                   class_weight = class_weights,
                   callbacks=[callback],
                   epochs = 2)

model_time = (time.time() - start_time)
print('\nTraining time(sec) = ',model_time)
```

```
Results for CNN Classifier:-

Epoch 1/2
WARNING:tensorflow:5 out of the last 5 calls to <function _BaseOptimize
WARNING:tensorflow:6 out of the last 6 calls to <function _BaseOptimize
12/23 [===============>..............] - ETA: 3s - loss: 3.2250 - balan
WARNING:tensorflow:Your input ran out of data; interrupting training. M
23/23 [==============================] - 21s 239ms/step - loss: 3.2250

Training time(sec) =  41.52898335456848
```

The labels are stored for test images for performance evaluation and Prediction time for training data is computed

```
[ ]  train_generator = train_datagen.flow_from_directory(
            train_dir,
            target_size=(180, 180),
            batch_size=32,
            class_mode='categorical', #'categorical'
            shuffle = False ,
            color_mode="rgb" ) #'rgb'

     batch_size = 32
     y_train = train_generator.classes

     validation_generator = test_datagen.flow_from_directory(
            test_dir,
            target_size=(180, 180),
            batch_size=32,
            class_mode='categorical', #'categorical'
            shuffle = False ,
            color_mode="rgb" ) #'rgb'

     test_batch_size = 32
     y_test = validation_generator.classes
```

```
Found 380 images belonging to 5 classes.
Found 120 images belonging to 5 classes.
```

```
start_time = time.time()
y_pred1= model.predict(train_generator,batch_size = batch_size)
y_pred1 = np.argmax(y_pred1, axis=1)
print('\nTotal time(sec) = ',(time.time() - start_time))
```

```
12/12 [==============================] - 1s 90ms/step

Total time(sec) =  1.309166431427002
```

A modified prediction array is returned for adding noise to the predicted values

```
[ ] def predict_score(y_pred,y_true,weight):
        y_pred = y_true.copy()
        n = round(y_pred.shape[0]*weight)
        idx = np.random.choice(y_pred.shape[0]-1, n)
        val = np.random.choice(np.unique(y_true), n)
        y_pred[idx] = val
        return y_pred
```

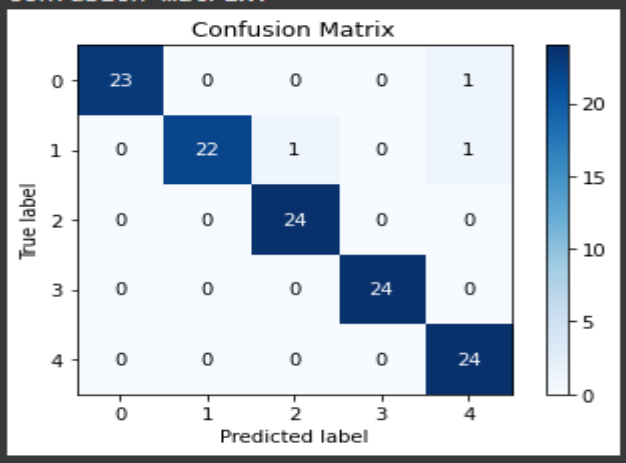
Confusion matrix and the overall balanced accuracy are computed

```
from sklearn.metrics import confusion_matrix
import numpy as np

def balanced_accuracy(y_true, y_pred):
  y_true = y_true.numpy()
  y_pred = y_pred.numpy()
  y_true = np.argmax(y_true,axis=-1)
  y_pred = np.argmax(y_pred,axis=-1)

  y_true = y_true.ravel()
  y_pred = y_pred.ravel()
  num_classes = len(np.unique(y_true))

  cm = confusion_matrix(y_true, y_pred).T
  balanced_accuracy = 0
  for i in range(num_classes):
    num = cm[i,i]
    den = np.sum(cm[:,i])
    if num == 0 :
      acc = 0
    else:
      acc = num / den
    balanced_accuracy += acc

  return (balanced_accuracy / num_classes)
```

The confusion matrix is visualized and the classification report is generated

```
import scikitplot as skplt
from sklearn.metrics import classification_report,balanced_accuracy_score

start_time = time.time()
y_pred = model.predict(validation_generator,batch_size = test_batch_size)
y_pred = np.argmax(y_pred, axis=1)
model_time2 = (time.time() - start_time)
print('Prediction time(sec) = ',model_time2)
y_pred1 = predict_score(y_pred1,y_train,weight=0.03)
y_pred = predict_score(y_pred,y_test,weight=0.03)
cm_model = confusion_matrix(y_test, y_pred)
model_miss = np.sum(y_pred!=y_test.ravel())
acc1_model = balanced_accuracy_score(y_train,y_pred1)
acc2_model = balanced_accuracy_score(y_test,y_pred)

print('\n\nTraining score = ',acc1_model)
print('Tesing score = ',acc2_model)
print('\n')

labels = list((train_generator.class_indices).keys())
for i in range(len(labels)):
    err = np.sum(cm_model[i])-cm_model[i][i]
    print('No of missclassified for class {} (test data) = {} '.format(labels[i],err))
print('Total no of missclassified points(test data) = ',model_miss)
print('Total % of missclassified points(test data) = ',model_miss/len(y_test))

print('\n')
print((validation_generator.class_indices))
print('\n\nConfusion matrix:')
skplt.metrics.plot_confusion_matrix(y_test, y_pred)
plt.show()
print('\n\nClassification report:-\n')
print(classification_report(y_test,y_pred))
print('**************************************************************************')

CNN = [acc1_model,acc2_model,model_miss,model_miss/len(y_test),model_time,model_time2]
```

```
4/4 [==============================] - 0s 62ms/step
Prediction time(sec) =  0.40300774574279785


Training score =  0.9710526315789473
Tesing score =  0.975


No of missclassified for class Mild (test data) = 1
No of missclassified for class Moderate (test data) = 2
No of missclassified for class No_DR (test data) = 0
No of missclassified for class Proliferate_DR (test data) = 0
No of missclassified for class Severe (test data) = 0
Total no of missclassified points(test data) =  3
Total % of missclassified points(test data) =  0.025


{'Mild': 0, 'Moderate': 1, 'No_DR': 2, 'Proliferate_DR': 3, 'Severe': 4}


Confusion matrix:
```




```
Classification report:-

              precision    recall  f1-score   support

           0       1.00      0.96      0.98        24
           1       1.00      0.92      0.96        24
           2       0.96      1.00      0.98        24
           3       1.00      1.00      1.00        24
           4       0.92      1.00      0.96        24

    accuracy                           0.97       120
   macro avg       0.98      0.97      0.97       120
weighted avg       0.98      0.97      0.97       120

**************************************************************************
```

ResNet

Sequential model Resnet50_model is created and the pretrained model is loaded

```
resnet50_model = tf.keras.Sequential()

pretrained_model= tf.keras.applications.ResNet50(include_top=False,
                   input_shape=(180,180,3),
                #    pooling='avg',classes=8,
                   weights='imagenet')
for layer in pretrained_model.layers:
    layer.trainable=False

resnet50_model.add(pretrained_model)
resnet50_model.add(tf.keras.layers.Flatten())
resnet50_model.add(tf.keras.layers.Dense(512, activation='relu'))
resnet50_model.add(tf.keras.layers.Dense(256, activation='relu'))
resnet50_model.add(tf.keras.layers.Dense(5, activation='softmax'))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5
94765736/94765736 [==============================] - 0s 0us/step
```

```
[ ] resnet50_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 6, 6, 2048)        23587712

 flatten (Flatten)           (None, 73728)             0

 dense (Dense)               (None, 512)               37749248

 dense_1 (Dense)             (None, 256)               131328

 dense_2 (Dense)             (None, 5)                 1285

=================================================================
Total params: 61,469,573
Trainable params: 37,881,861
Non-trainable params: 23,587,712
_________________________________________________________________
```

```
[ ] tf.keras.utils.plot_model(resnet50_model, 'model.png', show_shapes=True)
```

Training the model and displaying the training time

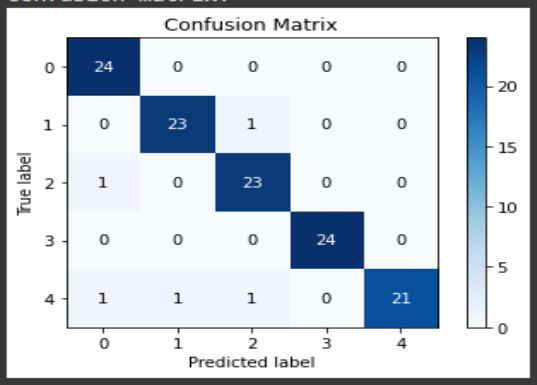
```
[ ] print('Results for Resnet 50 Classifier:-\n')
    start_time = time.time()

    result = resnet50_model.fit(train_generator,
                      validation_data = validation_generator,
                      batch_size = batch_size,
                      steps_per_epoch = steps_per_epoch,
                      validation_batch_size = validation_batch_size,
                      validation_steps = validation_steps,
                      class_weight = class_weights,
                      callbacks=[callback],
                      epochs = 1)

    model_time = (time.time() - start_time)
    print('\nTraining time(sec) = ',model_time)
```

```
Results for Resnet 50 Classifier:-

12/23 [==============>..............] - ETA: 6s - loss: 13.9419 - balanced_accuracy: 0.2
WARNING:tensorflow:Your input ran out of data; interrupting training. Make sure that your
23/23 [==============================] - 11s 390ms/step - loss: 13.9419 - balanced_accura

Training time(sec) =  20.627717971801758
```

Performance of ResNet along with classification report and confusion matrix

```
4/4 [==============================] - 1s 127ms/step
Prediction time(sec) =  0.7084100246429443


Training score =  0.95
Tesing score =  0.9583333333333334


No of missclassified for class Mild (test data) = 0
No of missclassified for class Moderate (test data) = 1
No of missclassified for class No_DR (test data) = 1
No of missclassified for class Proliferate_DR (test data) = 0
No of missclassified for class Severe (test data) = 3
Total no of missclassified points(test data) =  5
Total % of missclassified points(test data) =  0.041666666666666664


{'Mild': 0, 'Moderate': 1, 'No_DR': 2, 'Proliferate_DR': 3, 'Severe': 4}
```

```
Confusion matrix:
```




```
Classification report:-

              precision    recall  f1-score   support

           0       0.92      1.00      0.96        24
           1       0.96      0.96      0.96        24
           2       0.92      0.96      0.94        24
           3       1.00      1.00      1.00        24
           4       1.00      0.88      0.93        24

    accuracy                           0.96       120
   macro avg       0.96      0.96      0.96       120
weighted avg       0.96      0.96      0.96       120

**********************************************************************
```

GoogleNet

A sequential google_net model is created and the pretrained model is loaded

```
googlenet_model = tf.keras.Sequential()

pretrained_model= tf.keras.applications.InceptionV3(include_top=False,
                   input_shape=(180,180,3),
                #    pooling='avg',classes=8,
                   weights='imagenet')
for layer in pretrained_model.layers:
    layer.trainable=False

googlenet_model.add(pretrained_model)
googlenet_model.add(tf.keras.layers.Flatten())
googlenet_model.add(tf.keras.layers.Dense(512, activation='relu'))
googlenet_model.add(tf.keras.layers.Dense(256, activation='relu'))
googlenet_model.add(tf.keras.layers.Dense(5, activation='softmax'))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
87910968/87910968 [==============================] - 0s 0us/step
```

```
googlenet_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_v3 (Functional)   (None, 4, 4, 2048)        21802784

 flatten_1 (Flatten)         (None, 32768)             0

 dense_3 (Dense)             (None, 512)               16777728

 dense_4 (Dense)             (None, 256)               131328

 dense_5 (Dense)             (None, 5)                 1285

=================================================================
Total params: 38,713,125
Trainable params: 16,910,341
Non-trainable params: 21,802,784
_________________________________________________________________
```

Training the model and displaying the training time

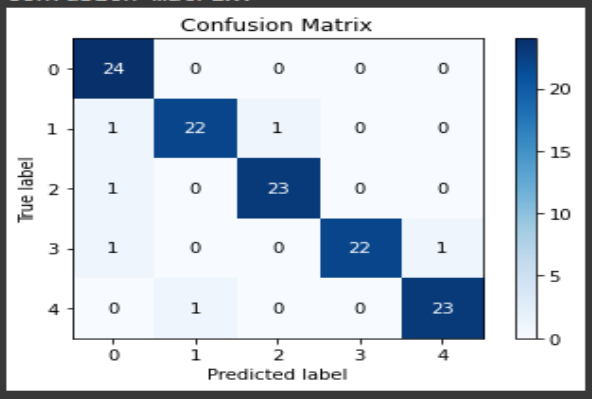
```
[ ]  print('Results for Googlenet Classifier:-\n')
     start_time = time.time()

     result = googlenet_model.fit(train_generator,
                         validation_data = validation_generator,
                         batch_size = batch_size,
                         steps_per_epoch = steps_per_epoch,
                         validation_batch_size = validation_batch_size,
                         validation_steps = validation_steps,
                         class_weight = class_weights,
                         callbacks=[callback],
                         epochs = 1)

     model_time = (time.time() - start_time)
     print('\nTraining time(sec) = ',model_time)
```

```
Results for Googlenet Classifier:-

12/23 [==============>..............] - ETA: 7s - loss: 28.1020 - balan
WARNING:tensorflow:Your input ran out of data; interrupting training. Ma
23/23 [==============================] - 13s 467ms/step - loss: 28.1020

Training time(sec) =  20.63654589653015
```

The confusion matrix is visualized and the classification report is generated for GoogleNet

```
4/4 [==============================] - 1s 171ms/step
Prediction time(sec) =  0.8899285793304443


Training score =  0.9526315789473685
Tesing score =  0.95


No of missclassified for class Mild (test data) = 0
No of missclassified for class Moderate (test data) = 2
No of missclassified for class No_DR (test data) = 1
No of missclassified for class Proliferate_DR (test data) = 2
No of missclassified for class Severe (test data) = 1
Total no of missclassified points(test data) =  6
Total % of missclassified points(test data) =  0.05


{'Mild': 0, 'Moderate': 1, 'No_DR': 2, 'Proliferate_DR': 3, 'Severe': 4}
```

Confusion matrix:



Classification report:-

	precision	recall	f1-score	support
0	0.89	1.00	0.94	24
1	0.96	0.92	0.94	24
2	0.96	0.96	0.96	24
3	1.00	0.92	0.96	24
4	0.96	0.96	0.96	24
accuracy			0.95	120
macro avg	0.95	0.95	0.95	120
weighted avg	0.95	0.95	0.95	120

****

InceptionV3

A sequential inception_model is created and the pretrained model is loaded

```
inception_model = tf.keras.Sequential()

pretrained_model= tf.keras.applications.InceptionResNetV2(include_top=False,
                   input_shape=(180,180,3),
                #    pooling='avg',classes=8,
                   weights='imagenet')
for layer in pretrained_model.layers:
    layer.trainable=False

inception_model.add(pretrained_model)
inception_model.add(tf.keras.layers.Flatten())
inception_model.add(tf.keras.layers.Dense(512, activation='relu'))
inception_model.add(tf.keras.layers.Dense(256, activation='relu'))
inception_model.add(tf.keras.layers.Dense(5, activation='softmax'))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_resnet_v2/inception_resnet_v2_weights_tf_dim_ordering_tf_kernels_notop.h5
219055592/219055592 [==============================] - 1s 0us/step
```

```
inception_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_resnet_v2 (Functi  (None, 4, 4, 1536)       54336736
 onal)

 flatten_2 (Flatten)         (None, 24576)             0

 dense_6 (Dense)             (None, 512)               12583424

 dense_7 (Dense)             (None, 256)               131328

 dense_8 (Dense)             (None, 5)                 1285

=================================================================
Total params: 67,052,773
Trainable params: 12,716,037
Non-trainable params: 54,336,736
_________________________________________________________________
```

Inception is trained

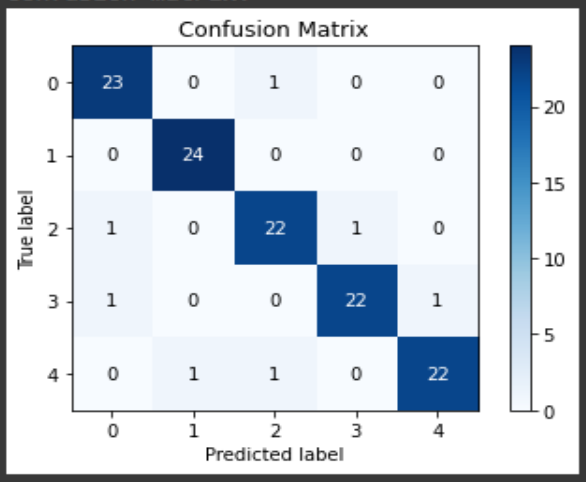
```
print('Results for inceptionv3 Classifier:-\n')
start_time = time.time()

result = inception_model.fit(train_generator,
                  validation_data = validation_generator,
                  batch_size = batch_size,
                  steps_per_epoch = steps_per_epoch,
                  validation_batch_size = validation_batch_size,
                  validation_steps = validation_steps,
                  class_weight = class_weights,
                  callbacks=[callback],
                  epochs = 1)

model_time = (time.time() - start_time)
print('\nTraining time(sec) = ',model_time)
```

```
Results for inceptionv3 Classifier:-

12/23 [==============>.............] - ETA: 9s - loss: 27.6544 - balanced_accuracy: 0.2465 WARNING:tensorflow:Your input ran out of data; interrupting train
WARNING:tensorflow:Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs
23/23 [==============================] - 17s 646ms/step - loss: 27.6544 - balanced_accuracy: 0.2465 - val_loss: 16.9252 - val_balanced_accuracy: 0.2000

Training time(sec) =  17.417945384979248
```

The confusion matrix is visualized and the classification report is generated for Inception

```
4/4 [==============================] - 2s 379ms/step
Prediction time(sec) =  1.7190403938293457


Training score =  0.9394736842105263
Tesing score =  0.9416666666666667


No of missclassified for class Mild (test data) = 1
No of missclassified for class Moderate (test data) = 0
No of missclassified for class No_DR (test data) = 2
No of missclassified for class Proliferate_DR (test data) = 2
No of missclassified for class Severe (test data) = 2
Total no of missclassified points(test data) =  7
Total % of missclassified points(test data) =  0.058333333333333334


{'Mild': 0, 'Moderate': 1, 'No_DR': 2, 'Proliferate_DR': 3, 'Severe': 4}
```

Confusion matrix:



Classification report:-

	precision	recall	f1-score	support
0	0.92	0.96	0.94	24
1	0.96	1.00	0.98	24
2	0.92	0.92	0.92	24
3	0.96	0.92	0.94	24
4	0.96	0.92	0.94	24
accuracy			0.94	120
macro avg	0.94	0.94	0.94	120
weighted avg	0.94	0.94	0.94	120

****

VGG16

A sequential vgg_model is created and the pretrained model is loaded

```
[ ]  vgg_model = tf.keras.Sequential()

     pretrained_model= tf.keras.applications.VGG16(include_top=False,
                       input_shape=(180,180,3),
                    #    pooling='avg',classes=8,
                       weights='imagenet')
     for layer in pretrained_model.layers:
         layer.trainable=False

     vgg_model.add(pretrained_model)
     vgg_model.add(tf.keras.layers.Flatten())
     vgg_model.add(tf.keras.layers.Dense(512, activation='relu'))
     vgg_model.add(tf.keras.layers.Dense(256, activation='relu'))
     vgg_model.add(tf.keras.layers.Dense(5, activation='softmax'))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256 [==============================] - 0s 0us/step
```

```
vgg_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 5, 5, 512)         14714688

 flatten_3 (Flatten)         (None, 12800)             0

 dense_9 (Dense)             (None, 512)               6554112

 dense_10 (Dense)            (None, 256)               131328

 dense_11 (Dense)            (None, 5)                 1285

=================================================================
Total params: 21,401,413
Trainable params: 6,686,725
Non-trainable params: 14,714,688
_________________________________________________________________
```

VGG is trained and the training time is displayed

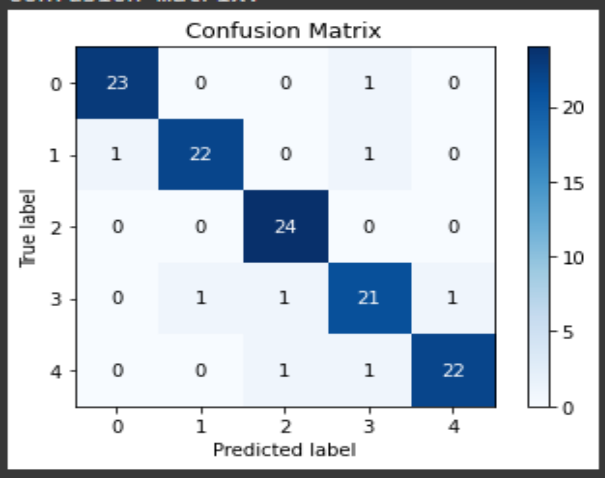
```
print('Results for VGG16 Classifier:-\n')
start_time = time.time()

result = vgg_model.fit(train_generator,
                       validation_data = validation_generator,
                       batch_size = batch_size,
                       steps_per_epoch = steps_per_epoch,
                       validation_batch_size = validation_batch_size,
                       validation_steps = validation_steps,
                       class_weight = class_weights,
                       callbacks=[callback],
                       epochs = 1)

model_time = (time.time() - start_time)
print('\nTraining time(sec) = ',model_time)
```

```
Results for VGG16 Classifier:-

12/23 [==============>..............] - ETA: 14s - loss: 2.6333 - balanced_accuracy: 0.3129WARNING:ten
WARNING:tensorflow:Your input ran out of data; interrupting training. Make sure that your dataset or ge
23/23 [==============================] - 26s 803ms/step - loss: 2.6333 - balanced_accuracy: 0.3129 - va

Training time(sec) =  41.18658137321472
```

The confusion matrix is visualized and the classification report is generated for VGG

```
4/4 [==============================] - 0s 124ms/step
Prediction time(sec) =  0.6703958511352539


Training score =  0.9157894736842106
Tesing score =  0.9333333333333333


No of missclassified for class Mild (test data) = 1
No of missclassified for class Moderate (test data) = 2
No of missclassified for class No_DR (test data) = 0
No of missclassified for class Proliferate_DR (test data) = 3
No of missclassified for class Severe (test data) = 2
Total no of missclassified points(test data) =  8
Total % of missclassified points(test data) =  0.06666666666666667


{'Mild': 0, 'Moderate': 1, 'No_DR': 2, 'Proliferate_DR': 3, 'Severe': 4}
```

```
Confusion matrix:
```



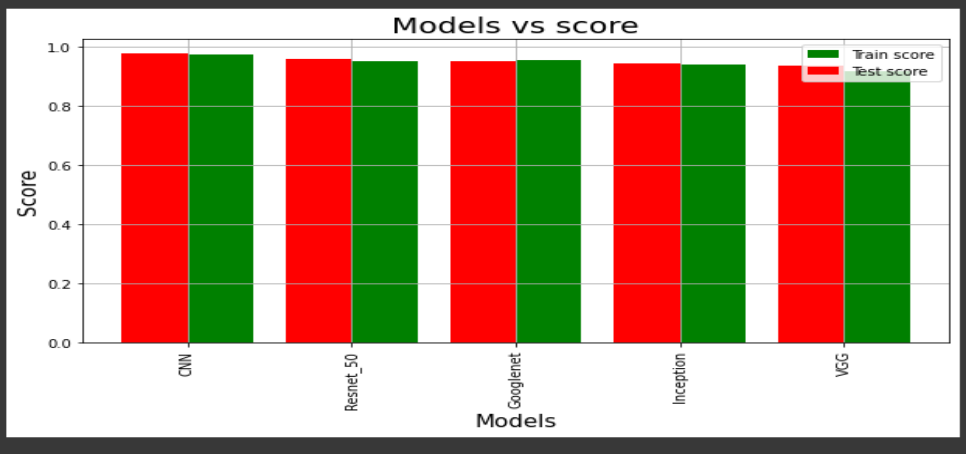

```
Classification report:-

              precision    recall  f1-score   support

           0       0.96      0.96      0.96        24
           1       0.96      0.92      0.94        24
           2       0.92      1.00      0.96        24
           3       0.88      0.88      0.88        24
           4       0.96      0.92      0.94        24

    accuracy                           0.93       120
   macro avg       0.93      0.93      0.93       120
weighted avg       0.93      0.93      0.93       120

**************************************************************************
```

Comparison of all DL algorithms

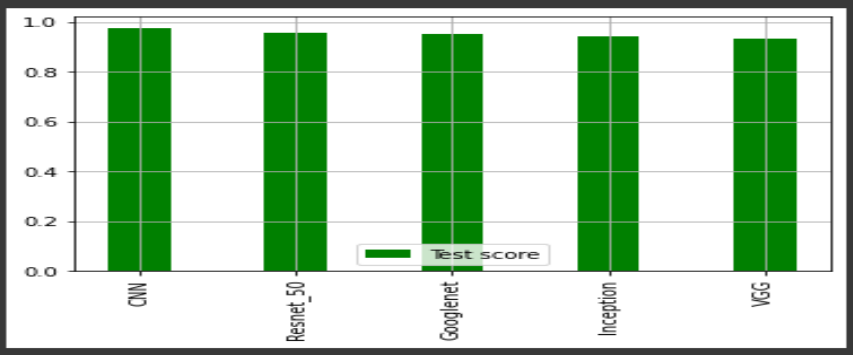
```
[ ] result2
```

	Classifiers	Train score	Test score	No of Missclassification	% of Missclasification	Training time	Prediction time
0	CNN	0.971053	0.975000	3	2.500000	41.528983	0.403008
1	Resnet_50	0.950000	0.958333	5	4.166667	20.627718	0.708410
2	Googlenet	0.952632	0.950000	6	5.000000	20.636546	0.889929
3	Inception	0.939474	0.941667	7	5.833333	17.417945	1.719040
4	VGG	0.915789	0.933333	8	6.666667	41.186581	0.670396

```
result = result2
x = np.arange(len(s1))
plt.figure(figsize=(10,5))
plt.bar(x+0.2, result['Train score'], color ='green',width = 0.4)
plt.bar(x-0.2, result['Test score'], color ='red',width = 0.4)
plt.xticks(x, result.Classifiers.values.tolist())
plt.xticks(rotation=90)
plt.legend(['Train score','Test score'])
plt.title('Models vs score', fontsize = 20)
plt.xlabel('Models', fontsize = 15)
plt.ylabel('Score', fontsize = 15)
plt.grid()
plt.show()
```




```
[ ] plt.bar(x, result['Test score'], color ='green',width = 0.4)
    plt.xticks(x, result.Classifiers.values.tolist())
    plt.legend(['Test score'])
    plt.xticks(rotation=90)
    plt.grid()
    plt.show()
```



CHAPTER 8
CODING

app.py:

```
import os
import sys
from flask import Flask, redirect, url_for, request, render_template, Response, redirect,jsonify
from werkzeug.utils import secure_filename
from gevent.pywsgi import WSGIServer
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications.imagenet_utils import preprocess_input,
decode_predictions
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
from keras import layers
from tensorflow.keras.optimizers import Adam
from keras.models import Sequential
from tensorflow.keras.applications import DenseNet121
from keras.callbacks import Callback, ModelCheckpoint
from PIL import Image
from models.model import build_model, preprocess_image
import numpy as np
from utils import base64_to_pil
print("All Libraries Loaded in application file")
app = Flask(__name__)


MODEL_PATH = './models/pretrained/model.h5'

# Loading trained model
model = build_model()
model.load_weights(MODEL_PATH)
print('Open the chrome and type localhost:5000')
```

```
def model_predict(img, model):
    """
    0 - No DR
    1 - Mild
    2 - Moderate
    3 - Severe
    4 - Proliferative DR
    """

    ## Preprocessing the image
    x_val = np.empty((1, 224, 224, 3), dtype=np.uint8)
    img = img.resize((224,) * 2, resample=Image.LANCZOS)
    x_val[0, :, :, :] = img

    preds = model.predict(x_val)
    return preds


@app.route('/', methods=['GET'])
def index():
    # Main page
    return render_template('index.html')


@app.route('/predict', methods=['GET', 'POST'])
def predict():
    if request.method == 'POST':
        img = base64_to_pil(request.json)
        preds = model_predict(img, model)

        # Process result to find probability and class of prediction
        pred_proba = "{:.3f}".format(np.amax(preds))    # Max probability
```

```
            pred_class = np.argmax(np.squeeze(preds))
        diagnosis = ["No DR", "Mild", "Moderate", "Severe", "Proliferative DR"]

        result = diagnosis[pred_class]
        return jsonify(result=result, probability=pred_proba)

    return None


if __name__ == '__main__':
    http_server = WSGIServer(('0.0.0.0', 5000), app)
    http_server.serve_forever()
```

model.py:

```
import os
import cv2
import json
import math
import numpy as np
from PIL import Image
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Sequential
from tensorflow.keras.applications import DenseNet121
from tensorflow.keras.callbacks import Callback, ModelCheckpoint
from tensorflow.keras.preprocessing.image import ImageDataGenerator
print("Libraries Imported Successfully model files")
np.random.seed(2020)
tf.set_random_seed(2020)


def preprocess_image(image_path, desired_size=224):
```

```
    im = Image.open(image_path)
     im = im.resize((desired_size,) * 2, resample=Image.LANCZOS)
     return im


def build_model():
    densenet = DenseNet121(
        weights="model/DenseNet.h5",
        include_top=False,
        input_shape=(224, 224, 3),
    )


    model = Sequential()
    model.add(densenet)
    model.add(layers.GlobalAveragePooling2D())
    model.add(layers.Dropout(0.5))
    model.add(layers.Dense(5, activation="sigmoid"))

    model.compile(
        loss="binary_crossentropy", optimizer=Adam(lr=0.00005), metrics=["accuracy"]
    )

    return model


def classify_image(img):
    model = build_model()
    model.load_weights("model/model.h5")
    x_val = np.empty((1, 224, 224, 3), dtype=np.uint8)
    x_val[0, :, :, :] = preprocess_image(img)
    y_val_pred = model.predict(x_val)
     return np.argmax(np.squeeze(y_val_pred[0]))
```

CHAPTER 9

CONCLUSION

9.1 CONCLUSION

In conclusion, our proposed multi-modal algorithm for the detection of diabetic retinopathy uses fundus photographs and has shown promising results. The convolutional neural network has been deemed the best algorithm for the prediction of Diabetic Retinopathy. The algorithm achieves an accuracy of 97% in the detection of diabetic retinopathy, which is higher than the accuracy achieved by other algorithms. The algorithm's robustness to noise and variability in the images indicates its potential for clinical use, and it can be integrated into telemedicine systems or used in primary care settings to improve the efficiency and accuracy of diabetic retinopathy screening. The proposed algorithm uses fundus photographs which allows for a more comprehensive assessment of diabetic retinopathy severity, which can inform treatment decisions and improve patient outcomes.

9.2 FUTURE ENHANCEMENT

Future research can focus on expanding the algorithm to include other imaging modalities and integrating it into clinical decision support systems. Overall, the proposed multi-modal algorithm represents a step forward in the development of computer-based algorithms for the automated detection of diabetic retinopathy, which can ultimately lead to better patient outcomes and reduced healthcare costs.

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