Interpretability of Diabetic Retinopathy Images using Grad-CAM

Submitted By

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Interpretability of Diabetic Retinopathy Images using Grad-CAM

Major Project - II

Submitted in partial fulfillment of the requirements

for the degree of

Master of Technology in Computer Science and Engineering

Submitted By

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Guided By

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Certificate

This is to certify that the major project entitled **"Interpretability of Diabetic Retinopathy Images using Grad-CAM"** submitted by **Asiya Durani (Roll No: 21MCEC17)**, towards the partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Engineering (CSE) of Nirma University, Ahmedabad, is the record of work carried out by him under my supervision and guidance. In my opinion, the submitted work has reached a level required for being accepted for examination. The results embodied in this major project part-II, to the best of my knowledge, haven't been submitted to any other university or institution for award of any degree or diploma.

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Statement of Originality

I, **Asiya Durani**, Roll. No. **21MCEC17**, give undertaking that the Major Project entitled "**Interpretability of Diabetic Retinopathy Images using Grad-CAM**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in **Computer Science & Engineering (CSE)** of Institute of Technology, Nirma University, Ahmedabad, contains no material that has been awarded for any degree or diploma in any university or school in any territory to the best of my knowledge. It is the original work carried out by me and I give assurance that no attempt of plagiarism has been made.It contains no material that is previously published or written, except where reference has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

Signature of Student

Date:

Place:

Endorsed by

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(Signature of Guide)

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Abstract

Diabetic retinopathy (DR) is one of the primary reasons for vision loss in people all over the world. The majority of those affected do not have access to expert ophthalmologists or the tools needed to monitor their condition, despite the fact that the disease is quite common. This can cause the start of the treatment to be delayed, which lowers their chances of having a favourable outcome. Deep learning methods that identify the disease in eye fundus photos have been offered as a way to make retinopathy moderate estimations more accessible to patients in remote locations or even as a way to supplement the diagnosis of a human expert in our experiment.In order to serve as a resource for both theorists and practitioners, this paper focuses on deep learning interpretability approache. More specifically, a literature review, and links to Grad-CAM method programming implementations are provided.

Abbreviations

DR	Diabetic Retinopathy.
CNN	Convolutional neural network.
G-CAM	Gradient-Weighted Class Activation Map.

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Chapter 1

Introduction

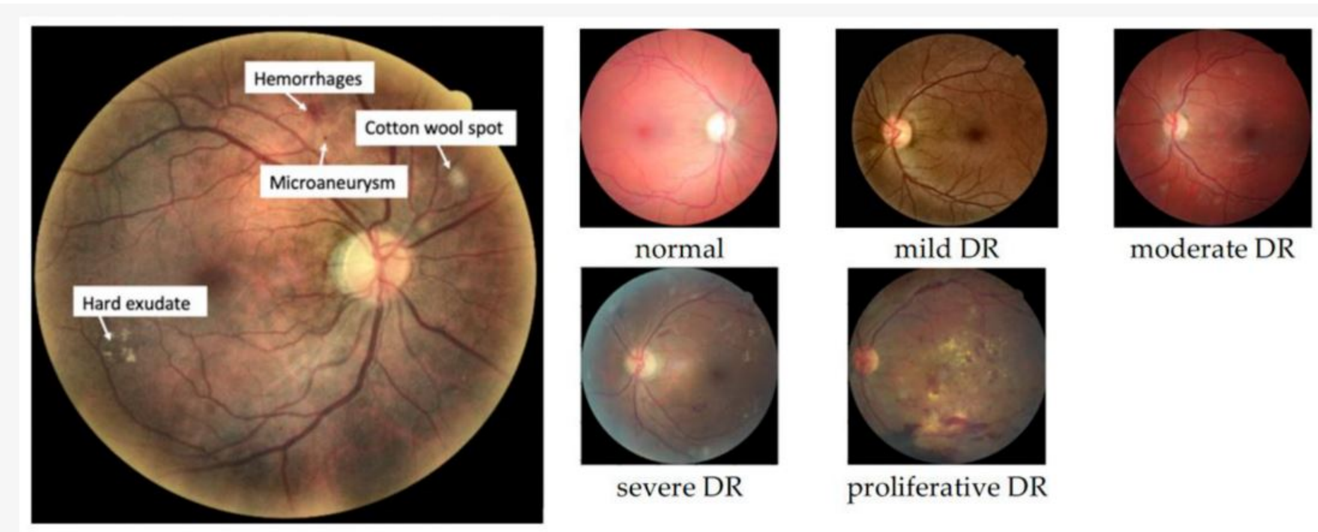
1.1 Knowledge Discovery Process

Diabetic retinopathy (DR), a consequence of diabetes, can cause blindness. In the long run, the likelihood that someone with diabetes would acquire DR rises to more than one in three. Despite the fact that diabetic eye disease is common, prompt treatment, that is, before major retinal damage, can greatly lower the chance of going blind. [2] Diabetic retinopathy comes in two different forms: (NPDR) non-proliferative, which mostly presents as retinal lesions, and proliferative (PDR), which also involves the neovascularization of weak blood vessels. Here, we present a technique for DR classification that involves patch-level fundus image analysis. First, a deep CNN model individually encodes each patch into a feature vector. Since human experts are more likely to believe a conclusion if they are aware of the motivations behind it, model interpretability is crucial for the effective adoption of a recommended ML solution in medical applications. Particularly in the case of DR, a model is typically treated as a "black box" during training and given interpretability properties the model's most sensitive fundus areas are visualised as a heatmap utilising some sort of post-training optimisation procedure.If we want to go deeper we have to Identify Interpretability methods and compare these methods with each other and then decide one of them,which would help to predict Diabetic as well as it give efficient result.

1.2 Diabetic Retinopathy

Diabetes frequently leads to diabetic retinopathy (DR), an eye condition. If untreated, it may damage the blood vessels in the retina, which might result in blindness.of essence, DR affects the blood vessels of the retina and other light-sensitive tissues. Today, it becomes the primary factor contributing to vision impairment and blindness among working-age adults worldwide [3].Even with diabetic macular edoema, DR's lack of an early warning indication is a well-known problem. Therefore, the ability to identify DR early is greatly desired. Unfortunately, the existing DR detection method practically cannot provide this requirement. Diabetes frequently results in diabetic retinopathy (DR), which impairs vision permanently. Clinical treatment can benefit greatly by early DR detection. Deep learning techniques have recently proliferated for evaluating medical images, producing cutting-edge outcomes. As a result, interpretable deep learning is now more important than ever. Although it has been shown that representation depth improves the accuracy of DR diagnosis classification. The current approach requires for a qualified clinician to manually evaluate digital colour fundus images of the retina. DR is identified by looking for lesions linked to vascular abnormalities brought on by diabetes, and the present method particularly calls for this.

Figure 1.1: lesions and classes of DR.[1]



The severity of diabetic retinopathy is based on there is a DR lesions, such as microaneurysms, haemorrhages, cotton wool patches, and exudates, as depicted in figure 1. In-person evaluations are impractical and unsustainable given the global increase in diabetes patients and the lack of retina experts. These tests could reveal DR too late, when treatment is less effective than in the early stages of the illness. Most people agree that CNN models are interpretable. Where did the networks search for distinguishing traits to recognise DR? Even though classification accuracy is crucial for automated diagnosis tasks.,it has grown more crucial and desirable to comprehend the logic behind the computer-assisted conclusion.

Symtoms of DR:

- floaters are spots or black threads that appear in your eyesight.
- vision that is hazy.
- unstable eyesight.
- sight loss.

Some of Interpretability methods are shown in 1.1[1]Occlusion:A perturbation technique is occlusion. A collection of input features are removed, changed, or otherwise perturbed using the perturbation approach. A The impacts on the output are then assessed after the second pass on the input characteristics. [2]Integrated Gradient: It is an interpretability approach that shows how important input features are in how the model predicts the future. By examining the change in this neuron as the input changes from the baseline input to the target input of interest, it is possible to determine the contribution of each input to the output neuron. [3]CAM: To determine which areas or pixels are more in charge of the model's output, the CAM analysis examines a fresh input image.Formally, CAM decodes a CNN by linearly integrating the activation maps from the last completely connected layer with the target class-specific fully connected weights from the final layer. [4]G-CAM:The CAM technique has been expanded by the Grad-CAM technique. The Grad-CAM follows the same steps as the CAM, but rather than just superimposing the visualisation on top of the original picture, it first determines the weighted sum of the activations (heatmap). [5]Layer wise relevance propagation: this method is an interpretability strategy that makes use of input variables to clarify specific predictions made by DL models.

Table 1.1: Interpretability Methods

Methods	Year	Description	Application
Layer wise Relevance Propagation (LRP)[4]	2019	The LRP technique allows for the direct identification of beneficial inputs to the network classification.	Alzheimer Disease Classification
Class Activation Maps (CAM)[5]	2021	Cancer classification, grading, and diagnosis are only a few of the uses for CAM. To identify the geographic areas that are most useful for choosing the right or wrong choice, they only developed a heat map for the projected class.	Oral cancer classification
Gradient-Class Activation Maps (Grad-CAM)[6]	2022	CNN Model	PCD
Network segmentation of 3D brain tumours with visual interpretation [7]	2020	To clearly evaluate the detection of radiological images and decide on the next action, they have used the Grad-CAM based color visualization approach.	chest X-ray and CT scan for the identification of COVID-19
Integrated Gradient (IG)[8]	2017	They analyse the relevance of features for this network using integrated gradients; just like in the object recognition scenario, the baseline is the black image.	Diabetic Retinopathy (DR) prediction
Occlusion[9]	2019	To determine the region's most responsible for the neural network's assignment of the projected diagnosis, an occlusion approach was carried out.	Age-related macular degeneration and diabetic macular edoema can be identified in OCT images.
Local interpretable Model-agnostic Explanations (LIME)[10]	2020	Give a LIME-based response to the aforementioned classification issue.	Parkinson's disease detection

Chapter 2

Literature Survey

2.1 Techniques

First We generalized all diseases in which Interpretability methods are used then we decide to go through Diabetic Retinopathy.After Deciding Disease we going to check interpretability methods that has many techniques to use in previous years paper in different medical experiment.We read number of paper which is describe below and found many methods.In this research significantly they used methods of Interpretability are Gradient weighted CAM,LRP,CAM.

2.2 Literature Survey: For All Diseases

So We summarize that many of these papers used Grad-CAM Methodology ,Grad-CAM is a one of the method of Interpretability.Grad-CAM (Gradient-weighted Class Activation Mapping) is a method used in deep learning and computer vision to detect and understand the areas of an image that a neural network model concentrates on while making predictions. It aids in understanding how a neural network makes decisions and sheds light on the elements of an input image that have the most influence on the projected class.Grad-CAM is frequently used in disease detection tasks, such as finding tumours, Covid-19, Diabetic Retinopathy, or lesions in medical images, as it offers interpretable visuals that can benefit clinicians and researchers in comprehending how a neural network is making predictions. Grad-CAM can provide light on the underlying features or patterns that the neural network is employing to diagnose a certain disease or abnormality by

Table 2.1: Literature Table

Paper	Year	Disease	Methodology / Technique	Dataset
An overview of comprehensible and accessible AI and its use in covid-19 imaging[11]	2022	Covid-19	Wrapper,Embedded/ PCA	Disease prognosis
Explainable and interpretable diabetic retinopathy classification based on neural-symbolic learning [12]	2022	Diabetic Retinopathy	ExplainDR method	IDRiD
Prediction Performance and Explainability of COVID-19 Classification Models [13]	2022	Covid-19	Grad-CAM / ResNet50V2, DenseNet169, Xception, and EfficientNet	CT-COVID
Network segmentation of 3D brain tumours with visual interpretation [7]	2021	Brain Tumor	Back-propagation, Grad-CAM,LIME	BraTS-2018
Considering Interpretability and Uncertainty in Brain Tumour Segmentation Networks [14]	2021	Brain Tumor	Gradient Weighted-CAM	BraTS-2018
Images of diabetic retinopathy were used in a visual interpretability study on Deep CNNs utilising an Adaptive Threshold technique. [15]	2021	Diabetic Retinopathy	Grad-CAM	IDRiD

showing the areas of an image that are contributing to a prediction. This can help in the creation of disease detection models that are more precise and explicable as well as in enhancing user confidence and knowledge of AI-based medical applications. Interpretability has many techniques to use in previous years in different medical experiment.

2.3 Literature Survey of Diabetic Retinopathy

In the table 2.2 we compare Grad-CAM method with different methods especially for Diabetic Retinopathy. After comparison We decide to go through Grad-CAM method to detect Diabetic Retinopathy.

In the first[14] paper,a fresh approach built upon the multiple instance learning (MIL) architecture to address this need by utilising the implicit information found in annotations. produced on an image-level basis. The proposed technique's primary contribution, in contrast to earlier MIL-based DR detection systems, is the result of combining the processes of instance encoding and image classification.Each picture on Messidor has two labels that display the clinical details and the DR rating. The presence and quantity of certain lesion types affect the probability of developing macular edoema.Prior to extracting and characterising, pre-processing was performed.The Messidor dataset has been extensively used in the literature to assess the efficacy of DR detection and grading techniques.Second paper [11],Despite being commonly used. They make no attempt to describe the model's representation learning process or the reasoning behind a specific prediction. Since DL approaches use a black box design architecture, The intended end users, such as ophthalmologists, have difficulty understanding how the models work, which hinders model acceptability for practical use. Several publications have been published on the interpretability of DL techniques used in DR-related tasks, such as DR classification and segmentation. We aim to give a comprehensive assessment of the interpretability techniques applied in DR-related activities with this paper.Third paper [6],they deploy the only openly available dataset that provides both lesion segmentation and disease severity gradings, the Indian Diabetic Retinopathy Image Dataset (IDRiD). The images have a resolution of 4288 $\times$ 2848 pixels. 1024 x 1024 pixels are the new size for each image. Four labels, including microaneurysms, hemorrhages, Soft exudates, and hard exudates, are present in the lesion segmentation dataset.In the fourth paper [9],They conducted two tests to categorise fundus pictures into normal and aberrant instances as

Table 2.2: Literature Survey:Diabetic Retinopathy

Paper	Year	Objective	Technique	Dataset
For the automatic recognition of diabetic retinopathy, towards understandable deep neural networks[16]	2022	Evaluated three splitting deep learning models	G-CAM	APTOS
Explainable and interpretable diabetic retinopathy classification based on neural-symbolic learning [12]	2022	Diabetic Retinopathy Detection	Benchmark	IDRiD
Analysis of diabetic retinopathy using deep learning interpretability techniques: a review [17]	2022	Overview of Interpretability methods		
A weakly-supervised framework for Interpretable Diabetic Retinopathy detection on retinal images [18]	2019	Detect DR Retinal Image	MIL,BOW	Messidor
Automated detection and diagnosis of diabetic retinopathy: A comprehensive survey [19]	2021	Review paper summarize 114 papers		43 datasets
Images of diabetic retinopathy were used in a visual interpretability study on Deep CNN utilising an Adaptive Threshold technique. [15]	2021	Diabetic Retinopathy	Grad-CAM	IDRiD

well as to classify the images according to the severity of the DR. The outcomes demonstrate the benefit of the VGG-16 model for binary and DR five-stage classification in terms of accuracy, precision, and recall. The models are not always capable of identifying DR-related lesions to determine a classification, despite the achieved accuracy of all evaluated models demonstrating their ability to capture some lesion patterns in the pertinent DR cases, according to a review of the models' explainability using the Grad-CAM-based colour visualisation approach.Last paper is the review paper summarise 114 published articles and 43 dataset.The review (2016–2021) covers the literature on AI approaches for DR, such as ML and DL in classification and segmentation, that has been published in the open literature during the past six years.

Chapter 3

Dataset

In this Chapter we explain dataset which we use in our implementation.originally, with 3664 and 1928 train and test images respectively.

3.1 APTOS

We used APTOS dataset which is easily available at kaggle.This would allow additional analysis and bench-marking comparison.Due to the fact that they were collected from numerous clinics using a variety of cameras spanning a considerable amount of time, this dataset contains a wide range of retinal pictures. A physician assigned a score to each photo according on the degree of DR present: 0 indicates normal, 1 mild, 2 moderate, 3 severe, and 4 indicates proliferative DR. This dataset's images might have artefacts or be out of focus. The quantity of diversity in this dataset rendered any type of classifier complex and difficult, hence it is imperative to test the models' findings. Unfortunately, because of the dataset's prior skewedness, the majority of samples fall into the category of usual healthy retina.This dataset's images might be fuzzy or include artefacts. It is crucial to confirm the models' conclusions because the quantity of diversity in this dataset made any classifier model complex and challenging. The majority of the samples, however, are in the normal, healthy retina class because the dataset was initially unbalanced. Moreover, no samples were designated as a validation set. There were only training and test sets .

The result of diabetes mellitus, diabetic retinopathy, damages the retina (the back of the eye) as a result of high blood sugar levels. Blindness could ensue from it if it is not properly detected and treated.The retina is a layer of light-sensitive cells in the back of

Table 3.1: Literature Table

Class	Labels	Count
0	No DR	1805
1	Mild	370
2	Moderate	999
3	Severe	193
4	Proliferative	295

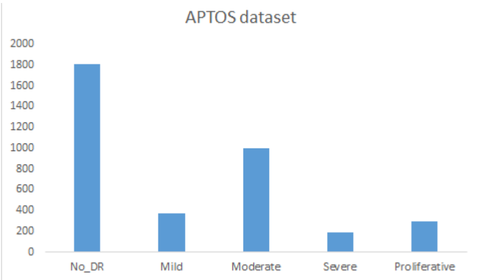


Figure 3.1: APTOS dataset

the eye that transforms light into electrical impulses.

3.2 Convolutional Neural Networks(CNN)

Using the Convolutional Neural Network (CNN), a deep learning method, image recognition and classification tasks.It is a kind of neural network built to recognise patterns in photos and automatically extract characteristics from them.The layers that make up CNNs include convolutional, pooling, and fully connected layers, to name a few. Pooling layers downs ample the feature maps whereas convolutional layers utilise filters to extract features from images. This lowers the computational cost of the network. Based on the retrieved features, the input image is classified using fully connected layers.By delivering cutting-edge performance in a range of image identification and classification tasks, including object detection, face recognition, and medical image analysis, CNNs have transformed the area of computer vision. They are very good at finding and recognising patterns in images. CNNs are particularly well-suited for diabetic retinopathy (DR) detection because the disease manifests as visible changes in the retina, such as microaneurysms, hemorrhages, exudates, and abnormalities in blood vessels.An enormous collection of retinal pictures is used to train a CNN, which may then be used to identify and categorise these DR-related visual patterns.The use of CNNs in DR detection has several advantages: 1.Automatic feature extraction: CNNs can learn and extract pertinent features automatically from retinal images, doing away with the requirement for manual feature engineering. This enables the network to adjust to various retinal defects linked to DR. 2.Highly accurate:In image classification problems, CNNs showed excellent performance, frequently exceeding conventional machine learning methods. They can identify DR symptoms with high accuracy in retinal pictures, allowing for early diagnosis and treatment. 3.Robust to variations:CNNs are built to accommodate visual variances such as distinct illumination, rotation, scale, and location. This qualifies them for the analysis of retinal images taken under various circumstances and using various imaging technologies. 4.Interpretability and visualization: CNNs can use methods like Grad-CAM to visualise the areas of an image that are important to the network's decision-making process. It helps physicians and researchers in comprehending the model's logic and gaining knowledge about the precise retinal properties taken into account for DR identification.

3.3 Gradient Weighted-Class Activation Map(Grad-CAM)

The Grad-CAM approach is a computer vision methodology for identifying and understanding the regions of an image that have the most impact on a convolutional neural network model's prediction. It helps in locating the areas of interest that affect how the model makes decisions. using a series of pooling and convolutional layers, the network in conventional CNN models extracts pertinent characteristics from the images before learning to classify them. Though it might be challenging to decide which elements of the image are most crucial for the prediction of the outcome. By generating a heat map that displays the regions of the input picture where the network's neurons are busiest, Grad-CAM overcomes this problem.Grad-CAM creates a weighted combination from the feature maps and gradients that identifies the parts of the image that most strongly affect the conclusion of the network.

Grad-CAM allows researchers and doctors to see the portions of the retina that contribute to the classification of retinal pictures as healthy or impacted by DR, making it particularly valuable in the identification of DR.The blood vessels in the retina might get damaged by high blood sugar levels., a condition known as diabetic retinopathy, which can cause vision loss or even blindness. Researchers can learn whether specific regions or features of the retina, such as microaneurysms, haemorrhages, or exudates, are being taken into account by the model for DR detection by applying the Grad-CAM approach to a CNN trained on a large dataset of retinal pictures. Understanding the underlying patterns and biomarkers that contribute to the disease's presence can be aided by this information. Additionally, it might enhance the predictability, interpretability, and reliability of the model in clinical contexts.

Chapter 4

Proposed Methodology

4.1 Description of Architecture

In below model architecture 4.1 we applied many convolution layers which is describe below:

- Artificial input neurons make up the neural network's input layer, which communicates the system's initial set of data into deeper layers of deep neurons for processing. The input layer represents the very first step in the neural network's operation.In our architecture this layer defines the input shape of the model.

- Data augmentation :is the act of creating new information artificially using training data that has already been gathered. Cropping, cushioning, flipping, rotating, and resizing are examples of techniques. It fixes issues like overfitting and data shortage while enhancing the model's performance.In order to make the network robust to these often occurring events, the Data Augmentation technique is applied. By rotating input images at different angles, flipping images along other axes, or translating/cropping the images, the network will encounter these occurrences during training. Our model's data augmentation techniques are applied to the input data at this layer.

- Patches: Instead of processing the entire image, CNN kernels/filters only process one patch at a time. This is so that filters may analyse discrete portions of the image to identify features (such as edges, etc.). Since we're estimating fewer parameters and those parameters need to be "good" across many areas of each image as well as many regions of all previous training photos, this also has a great regularisation property.This layer creates sections of the input image that are a certain size.

- Patch Encoder: The diagram of the patches in the given model must be transformed into a more meaningful representation by the patch encoding layer in order for the subsequent Transformer layers to process it properly.Patch-level features are projected and transformed into a higher-dimensional space by the patch encoding layer, which is also known as the ”embedding space” or ”latent space.” The model can now capture intricate relationships and patterns within the patches thanks to this modification, which is significant. normalisation: Instead of in the raw data, normalisation occurs between the layers of a neural network. Instead of using the entire data set, it is done in small portions. It improves learning by accelerating instruction and utilising quicker learning rates.

- A pre-processing method for standardising data is normalisation. being able to compare the ranges of multiple data sources. Our network may experience issues, making training much more challenging and reducing its learning rate, if the data is not normalised before training.

  This layer performs batch normalisation on the encoded patches.

- Flatten: The input tensor in the specified model is flattened into a 1-dimensional tensor using the Flatten layer. The input tensor, which may have several dimensions, is transformed into a single continuous vector.The output of earlier layers is frequently a multi-dimensional tensor in convolutional neural networks (CNNs) or models that handle spatial data, typically with dimensions denoting the batch size, height, breadth, and channels. But occasionally, we could wish to send this tensor to a fully linked layer or another kind of layer that only accepts inputs in one dimension.This is accomplished by flattening the tensor’s dimensions into a single dimension.

- Dropout:Another significant CNN feature is a dropout layer. Similar to a mask, the Dropout layer preserves the functioning of all other neurons while removing particular neurons’ contributions to the layer above.In this layer, dropout regularisation is applied on the flattened representation tensor.

- Output Layer: Every cell in the layer of neurons, which is the layer underneath the dense layer, conveys information to every neuron in that layer. Based on the results of the convolutional layers, the photographs are classified using a dense layer. activity of a single neuron. Within a layer, there are several such neurons.This layer is dense (fully linked), features num-classes units, and a softmax activation function. The final output logits of the model are produced by it.

4.2 Model Architecture

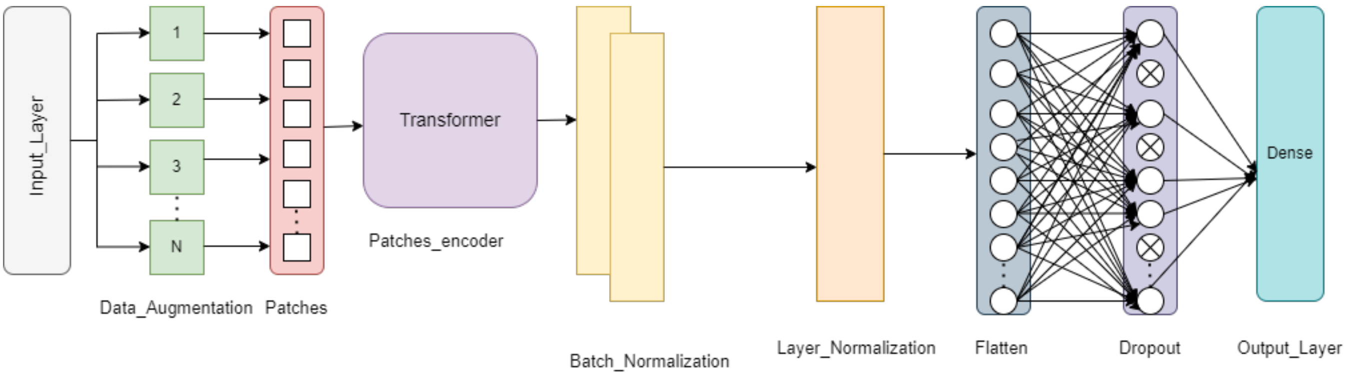


Figure 4.1: Proposed Model

Chapter 5

Result of Experiment

5.1 Confusion matrics

In figure 5.2 5.3 provide knowledge about the model's performance during training by showing the accuracy and loss curves over 100 epochs. While the loss plot shows the progression of training and testing loss, the accuracy plot displays the progression of training and testing accuracy. As training goes on, these visualisations assist in determining if the model is improving or overfitting.

	precision	recall	f1-score	support
0	0.94	0.96	0.95	361
1	0.48	0.45	0.46	74
2	0.64	0.69	0.66	200
3	0.47	0.23	0.31	39
4	0.40	0.39	0.39	59
accuracy			0.75	733
macro avg	0.58	0.54	0.56	733
weighted avg	0.74	0.75	0.74	733

Figure 5.1: Confusion matrics

We may evaluate a binary classifier model's performance by plotting the AUC measure shown in figure5.4. Area Under the Receiver Operating Characteristic (AUC) Curve (ROC) quantifies the trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) at various categorization thresholds. AUC stands for Receiver Operating Characteristic (ROC) curve. AUC is a measure of how well a classifier performs, with 1 being the optimal value.

The graphic enables us to see how the AUC for both the training and Testing sets

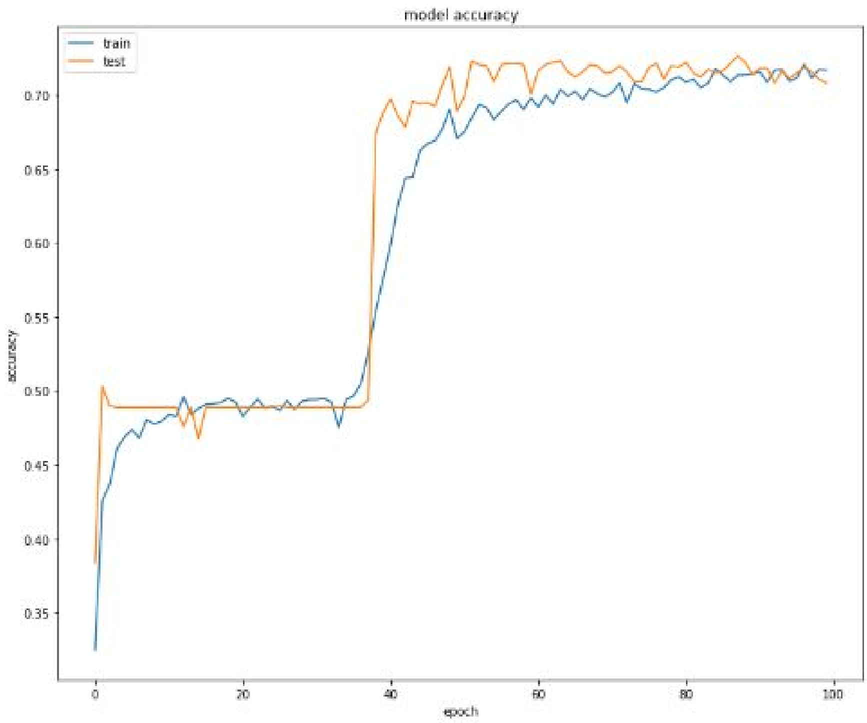


Figure 5.2: Accuracy

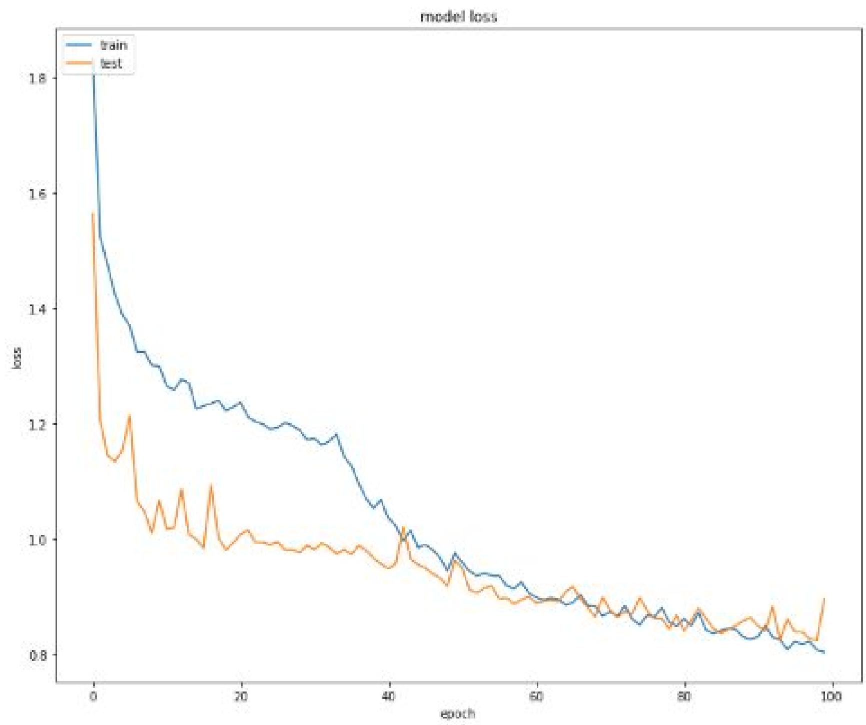


Figure 5.3: Loss

varies over epochs. Throughout the training process, we may evaluate the model's capability to distinguish between positive and negative samples by keeping an eye on the AUC. It sheds light on the model's overall effectiveness and shows if it is improving or

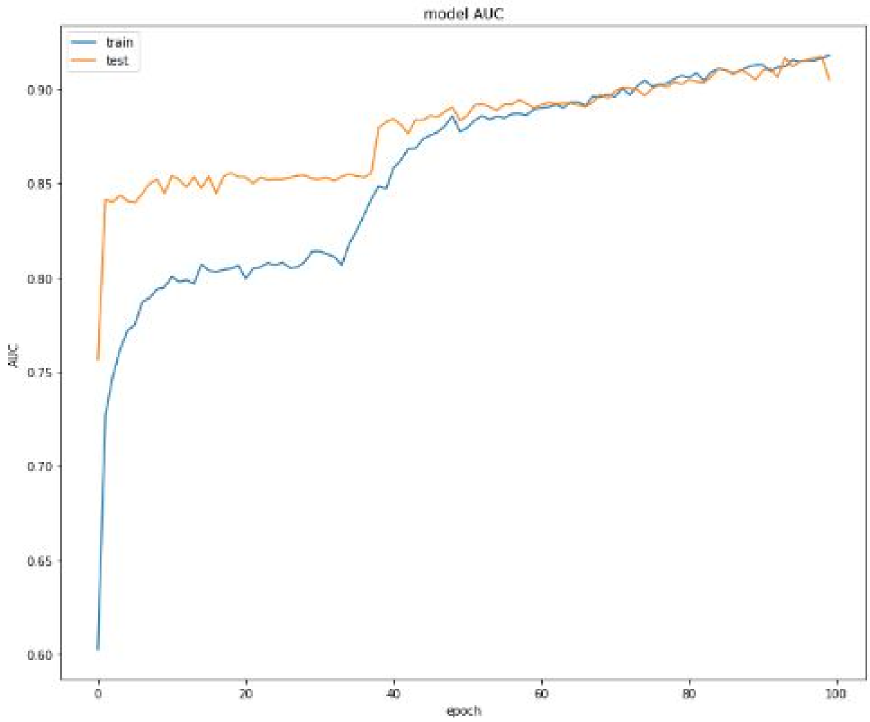


Figure 5.4: AUC

becoming overfit to the training set of data.

5.2 Visualization of Image

Figure 5.5: Image

The first image 5.5 shows the original image from the dataset along with its shape, information on its patches, and an image patch grid. The extracted patches which is shown in 5.6 represented visually in the grid, with n patches displayed in each row and

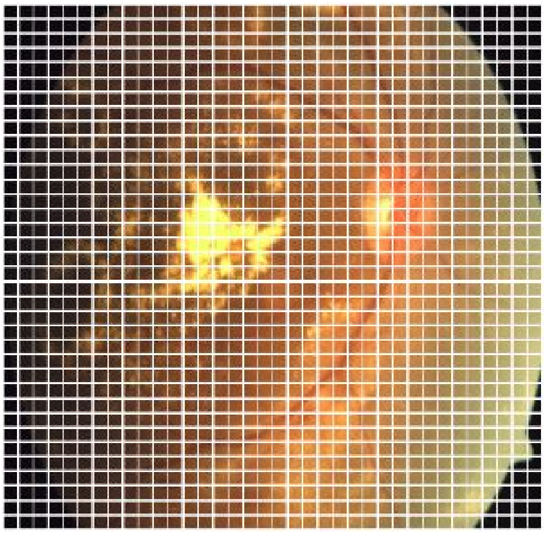


Figure 5.6: No of Patches of Image

column.

5.3 Result Analysis of Grad-CAM

The portions of the input image that allow the majority of the prediction are highlighted by the grad-cam heatmap function using gradients of the top predicted class relative to the output of the final convolutional layer.The input image for which a Grad-CAM heatmap must be produced is img-array. model: The model that is used to create the heatmap. Name of the final convolutional layer in the model, last-conv-layer-name. pred-index: The projected class's index, which is optional. The top anticipated class index is used if none are given.Using the tf.keras.models, the code first builds a new model called grad-model.model group. This model outputs the activations of the last convolutional layer from the input image.Within a gradient tape, the function calculates the gradient of the top predicted class (or the chosen pred-index) in relation to the activations of the final convolutional layer. The variables last-conv-layer-output and preds, respectively, are used to record the results of the most recent convolutional layer and the predictions.The heatmap is then divided by its maximum value and any negative values are clipped before being normalised between 0 and 1 for visualisation reasons.The created heatmap is then returned by the function as a NumPy array.

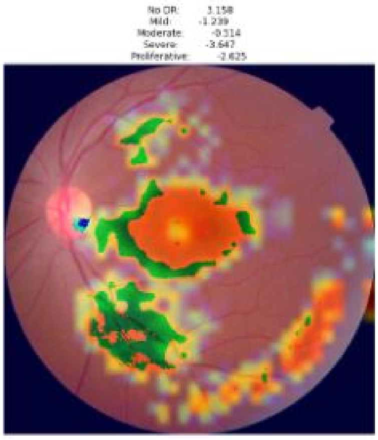


Figure 5.7: Predicted Result

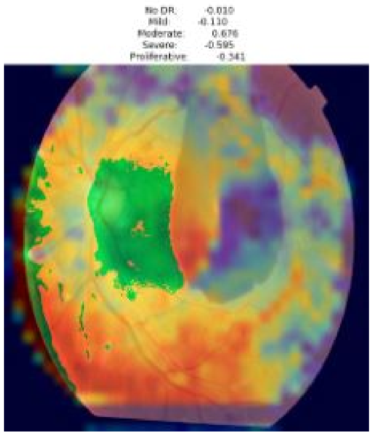


Figure 5.8: Predicted Result

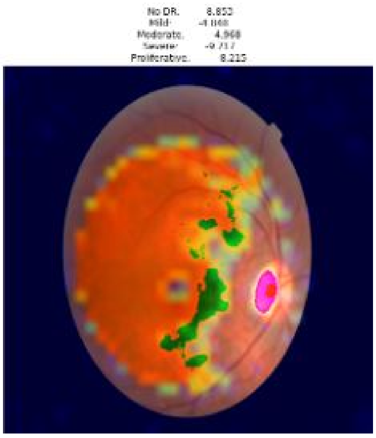


Figure 5.9: Predicted Result

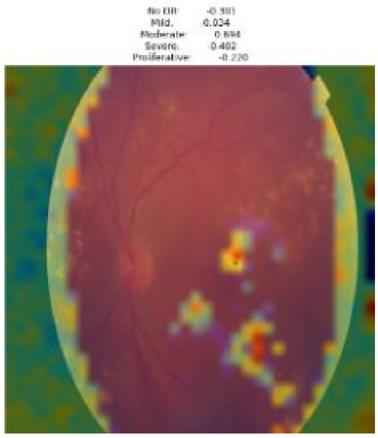


Figure 5.10: Predicted Result

Chapter 6

Conclusion

To conclude our report,Using a dataset of retinal pictures, we evaluated DR and five-stage classification models. In order to expand the amount of the data and produce reliable results, we first performed the preprocessing stage. Then, from the dataset, we select one image and divide it into a number of patches.After that, we trained, built, and evaluated our model to determine accuracy, loss, and AUC.The proportion of model attention to DR indicators is measured by the suggested metric using the Grad-CAM technique. Model overcame the competition in terms of conformance and demonstrated much more reasonable conclusions.

Future work will evaluate deep learning model explainability and interpretability using our proposed measure, and it will combine lesion detectors with a general classifier to get more understandable classification results.

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