Diabetic Retinopathy using Gaussian Filter

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Abstract*— The retina is an essential component of the visual system, and maintaining eyesight depends on the timely and correct detection of disorders. Identification of minute alterations that are difficult to spot during conventional eye exams is made possible by the analysis of retinal pictures. Our work aims at building strong deep learning models such as InceptionV3, DenseNet121 and other CNN based models that can detect subtle pathological alterations and use that information to estimate the risk of retinal illnesses. We specifically address the early detection and severity classification of diabetic retinopathy (DR), a serious public health hazard. Our objective is to improve the diagnostic processes for diabetic retinopathy, the primary cause of diabetes-related blindness, by utilizing deep learning models. The datasets used was the Diabetic Retinopathy 224X224 Gaussian Filtered and the Diabetic Retinopathy 224X224 Greyscale Images with 3662 retinal images each and corresponding classes of severity of the disease. A comparative analysis between Greyscale, Gaussian and Gabor filters has been provided after applying these filters on the fundus images. We obtained an accuracy of 84% with InceptionV3 on Gaussian images therefore Gaussian filter emerged as our most promising filter.

***Keywords*— Severity prediction, InceptionV3, Gaussian Filter, Gabor Filter**

I. Introduction

Diabetic retinopathy (DR), an inflammatory condition affecting the retina (the light-sensitive tissue in the back of the eye), is one of the most prevalent and potentially blinding complications of diabetes mellitus. Degenerative conditions such as diabetic retinal disease (DR) are characterized by vascular injury to the retina, primarily brought on by prolonged high blood sugar levels. More than one-third of individuals with diabetes experience some kind of diabetic retinopathy; if managed, this condition can worsen from moderate non-proliferative abnormalities to proliferative diabetic retinopathy (PDR), which can be blinding, and diabetic macular edoema (DME). By 2030, over 11 million people worldwide are predicted to suffer from advanced diabetic retinopathy due to the rising incidence of diabetes. When abnormal blood vessels emerge, the sickness manifests in stages ranging from mild non-proliferative alterations to severe proliferative alterations. Accurate severity classification and early diagnosis of diabetic retinopathy are critical for successful therapeutic intervention and prevention of permanent visual loss.

The convergence of medical science and artificial intelligence has resulted in a paradigm shift in the diagnosis and management of diabetic retinopathy in recent years. Traditional procedures frequently struggle to provide complex severity classifications, and more advanced methodologies are desperately needed. This study aims to close the gap by introducing a novel categorization approach that overcomes the constraints of existing automated grading systems. We hope to develop a robust and efficient tool for discriminating diabetic retinopathy severity stages by leveraging the potential of deep learning, specifically convolutional neural networks (CNNs). This method not only offers improved accuracy, but it also aims to address the clinical care spectrum, which includes the five expert-defined severity stages. Our goal as we delve into the intricate aspects of retinal images and use the possibilities of modern technology is to contribute to the refining of diagnostic methods, ultimately increasing the standard of care for diabetic retinopathy patients.

The advancement of deep learning technology, particularly convolutional neural networks (CNNs), has made it feasible to automate the analysis of retinal imagery. This has made the process of detecting diabetic retinopathy more accurate and efficient.

The main goal of this project is to develop a methodology for categorizing retinal images that will be more effective at discriminating between the five different severity classifications of diabetic retinopathy than the automated grading systems that are currently in use. Currently, most published models simplify the disease category for binary identification of diabetic retinopathy without considering the degree of development. Although some studies classified three grades, few studies distinguish between the five expert-defined severity stages that directly affect clinical care: no apparent retinopathy, mild, moderate, severe non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR).

The paper is structured as follows: Section II describes the literature survey which mentions various methods used to similar to the ones presented in this paper and discussing their work. Section III introduces the data andhow it was gathered along with its understandings. Section IV discusses about the methodology that has been employed in this paper. This is followed by discussion of the results andtheir analysis and lastly, Section VI talks about the conclusion and future scope.

II. Literature Survey

The CNN architecture and its variations were proposed in a number of papers for multi-label disease classification on both public and private datasets. A deep learning platform (DLP) for the identification of 39 fundus illnesses and disorders was created by Cen et al. [1]. They reported an AUC value of 0.99 using a combination of publicly accessible EyePACS dataset and proprietary datasets gathered from various parts of China. Ju et al. [2] trained a ResNet-50 [3] using a hybrid distillation technique, obtaining knowledge from two teachers who had been taught using various sampling techniques. This method classified 50 types of diseases using two private datasets with 100,000 and one million photos, respectively. The mean Average Precision (mAP) score that they finally published was 64.14% and 64.69% for the 100K and 1 million images.

The Diabetic Retinopathy (DR) level in humans is identified by looking for hemorrhages and exudates on the image of the human body. The authors in [4] SVM classifier is trained using a few images of the human body that display the different DR layers. In order to determine whether the input image is traditional or has DR, the alternatives will be extracted below the classification half. The classifier appropriately classifies the degree of DR supported by the SVM Classifier's coaching using the input check picture. In [5], the images are subjected to multi-class SVM and KNN classifiers in order to ascertain the degree of irregularity. The writers have conducted tests using Diabeticret DB and MESSIDOR. The optic disc is taken out and the photos are preprocessed using GLCM, features for categorization are extracted.

The development of computer-aided detection mechanisms for identifying abnormalities in retinal imaging and identifying the presence of abnormal features from retinal fundus pictures is the main emphasis of Raman et al. [6]. Their suggested methodology focuses on improving images, removing noise, detecting blood vessels and identifying the optic disc, extracting exudates and microaneurysms (MA), extracting features, and using machine learning techniques to classify different stages of diabetic retinopathy as mild, moderate, severe, NPDR (Non-Proliferative Diabetic Retinopathy), and PDR (Proliferative Diabetic Retinopathy). In [6] Zhao et al., presented a novel saliency-based method in their work for identifying fluoresce leakage in angiography.

Diabetic Retinopathy and Malarial Retinopathy are the only two publically available datasets used to validate their suggested methodology. In order to detect blood vessels, microaneurysms, and other abnormalities, Prasad et al. suggested using segmentation algorithms in conjunction with morphological operations.For better feature selection, the Principal Component Analysis, or PCA [7], is used. Moreover, one-rule classifiers and back-propagation neural networks were used to classify photos as either diabetic or non-diabetic. The method used by M. Usman Akram et al. [8] is based on a hybrid classifier that detects retinal lesions through preprocessing, lesions extraction from candidates, feature formulation, and classification. In order to increase classification accuracy, the work expands on the m-Mediods based modeling methodology by fusing it with the Gaussian Mixture Model to create a hybrid classifier. Gardner and colleagues investigated if neural networks could identify the diabetes characteristics present in the [9] fundus photos and compared the network to an ophthalmologist screening set of the fundus photographs. The investigation demonstrated the identification of vessels, exudates, and hemorrhages. In addition, their network achieved greater accuracy in detecting diabetic retinal impairment as compared to ophthalmologists. In their research, Roychowdhury et al. employed Adaboost to rank features, which helped reduce the number of features needed for the [10] lesion classification.

Segmentation of these features and blood vessels are subjects of research in this field [11], [12]. DR fundus image classification has advanced quickly in recent studies, with deep neural network topologies initially proposed as a solution for natural picture categorization. A CNN (LeNet-5) model is used by Wang et al. [10] to extract picture features in order to address blood vessel segmentation. There are certain restrictions with these techniques. First off, the accuracy of the features in the dataset cannot be guaranteed due to their manual and empirical extraction. Secondly, the quality and amount of the data sets are limited, typically consisting of only a few hundred or even hundreds of fundus images collected in a relatively specific environment. This makes it impossible to compare the algorithms' performance across the experiment.

With the introduction of the AlexNet architecture by Alex et al. [14], [15], for notable performance gains during the 2012 ILSVRC competition, deep CNNS has become widely used in computer vision. Following the proposal of several superior CNN architectures, including VggNet [16, 17], and GoogleNet [18]. ResNet [3], one of the most significant network models, was put forth in 2015 and improves upon CNN performance in image categorization.

The primary aim of this research is to conduct a comparative analysis of the filters applied to the dataset with a focus on identifying and assessing those that yield optimal results. Through a systematic examination of various filters, the study aims to discern and highlight the most effective ones in enhancing the dataset. This investigation is geared towards advancing our understanding of the impact of different filtering techniques, ultimately contributing valuable insights to the field and informing best practices in data processing.

III. Data Description

The dataset includes 3664 retinal images that highlight different phases of diabetic retinopathy, a consequence of diabetes that is the main cause of visual impairment. The images show the evolution of an illness and are divided into five graded classes namely, Mild, Moderate, No_DR, Proliferate_DR and Severe which were labelled by medical specialists. The images are downsized to 224 × 224 pixels, which are the suitable dimensions for feeding them into deep learning neural networks. As seen in Fig 1., images having no sign of disease consume most of the dataset, and therefore the dataset is imbalanced.

Therefore, augmentation was done on the images. The applied image augmentation strategy encompasses pixel normalization for values within [0, 1], coupled with random horizontal and vertical shifts of up to 20% during training. This intentional perturbation introduces spatial diversity, simulating real-world variations. The strategy aims to mitigate overfitting by exposing the model to a spectrum of transformed images, fostering better generalization. Additionally, 20% of the dataset is allocated to a validation subset for robust model evaluation.

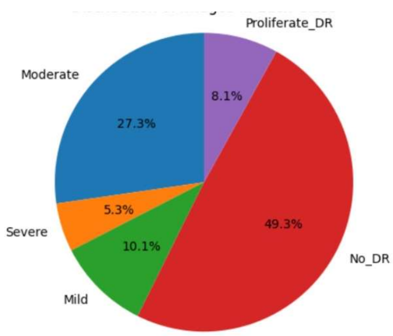

Fig 1. Original Distribution of Images

After augmentation, three distinct filters were applied, namely Gaussian, Grayscale, and Gabor, and then their impact was evaluated using various models. The grayscale and gaussian images were already available in the dataset.

A. Gaussian

The Gaussian filter shown in Fig. 2. (i), effectively smooths irregularities and reduces noise, particularly enhancing structures relevant to diabetic retinopathy such as blood vessels and lesions. By prioritizing pixel weights based on proximity, the filter contributes to the extraction of meaningful features crucial for classification. The preprocessed images then undergo feature extraction, capturing distinctive patterns indicative of diabetic retinopathy.

$$G(x,y)= \frac{1}{2\pi\,\sigma^2} \exp(-\frac{x^2+y^2}{2\,\sigma^2})$$

G(x) =Value of the Gaussian function at position (x,y) in the image
σ=8 (standard deviation of the Gaussian envelope)

B. Greyscale

The grayscale filter on the eye shown in Fig. 2 (ii) proves advantageous for analyzing retinal eye images by simplifying data and enhancing contrast. This conversion to a single intensity channel streamlines image processing, making it compatible with various analysis techniques and reducing computational complexity. The resulting grayscale images offer improved visibility of critical anatomical structures, such as blood vessels, lesions, or abnormalities. The pixel intensities range from 0 to 255, 0 being black and 255 being white.

C. Gabor Filter

The Gabor filter shown in Fig. 2. (iii) is distinguished by its exceptional capacity to capture complex texture patterns in a variety of orientations and scales. In contrast to normal filters, the Gabor filter excels at picking up on minute characteristics related to diabetic retinopathy, like changes in blood vessel and microaneurysms. This is because it mixes a sinusoidal function with a Gaussian envelope. Because of its unique feature extraction capacity, the Gabor filter is very useful for bringing attention to subtle textures that are suggestive of the illness. In contrast to traditional filters, the Gabor filter improves the accuracy of diabetic retinopathy diagnosis in retinal pictures by highlighting these particular patterns, which leads to a more sophisticated and sensitive categorization technique.

$$G(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp(-\frac{x'^2+\gamma^2 y'^2}{2\,\sigma^2})\cos(2\pi\frac{x'}{\lambda} +\psi)$$

G(x,y)=filter response at position (x,y)
x’=xcos(θ)+ysin(θ)
y’= -xsin(θ)+ycos(θ)
λ=10 (wavelength of sinusoidal factor)
θ=45 degrees (orientation of the filter)
σ=8 (standard deviation of the Gaussian envelope)
γ=0.5 (spatial aspect ratio, which stretches the filter along one direction)
ψ=2 (Phase offset of sinuoisoidal factor)

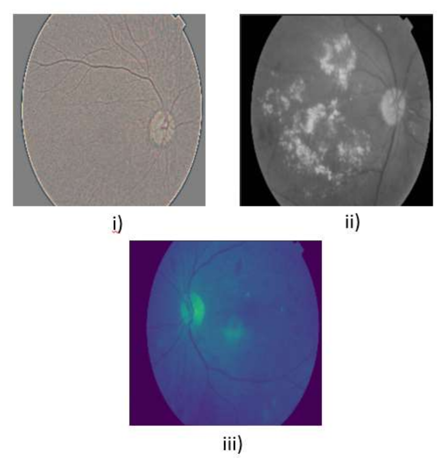

Fig 2. Filters applied on the images i) Gaussian ii) Grayscale iii) Gabor

D. System Architecture

The process of analyzing retinal pictures with deep learning models and different filters is depicted in the diagram

Fig. 4. Retinal images are used as the input and these images are resized to 224x224 and augmented. The augmented photos are then subjected to three filters: the Gaussian, grayscale, and gabor filters. With the aid of these filters, particular picture characteristics that are pertinent to the categorization of diabetic retinopathy can be extracted.

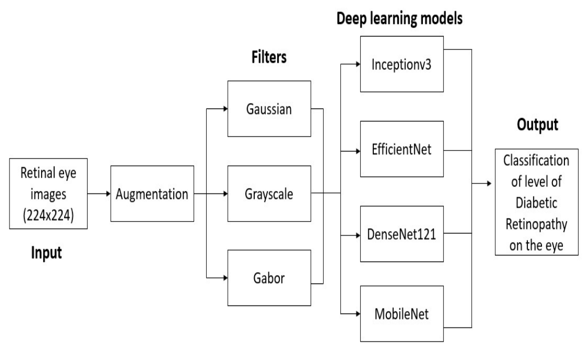

Fig. 3. Proposed System Architecture

The four deep learning models Inceptionv3, EfficientNet, DenseNet, and MobileNet are fed the pre-processed photos. These models are intended to evaluate the information retrieved by the filters and forecast whether or not diabetic retinopathy will be present in the retinal images, as well as how severe it will be.

IV. METHODOLOGY

The paper provides a comparative analysis using two different filters, namely the gaussian filter and the gabor filter, where both filters are applied to the original grayscale photos and fed into the four subsequent models to provide a comparative study.

A. EfficientNet B0

EfficientNet B0 functions as a feature extractor in the context of diabetic retinopathy classification, leveraging its pretrained weights to comprehend the intricacies of retinal pictures. The model is fine-tuned for the task by including two additional layers: a Flatten layer to reshape the multidimensional output and a Dense layer with SoftMax activation to classify five severity stages. This transfer learning technique improves model parameters for the diabetic retinopathy problem, guaranteeing that the model uses prior knowledge while adapting to the complexities of severity categorization.

B. Inceptionv3

The model shown in Fig. 4., which has been fine-tuned for diabetic retinopathy, has two extra layers—a Global Average Pooling layer and a Dense layer with SoftMax activation—to predict five severity classifications. The InceptionV3 model has a total of 21,813,029 parameters, of which 21,778,597 are trainable and 34,432 are not. These parameters are distributed across the model's tiers. The non-trainable parameters mostly correspond to the InceptionV3 backbone, which has acquired generic features from ImageNet before adding the extra layers for diabetic retinopathy classification. The additional layers improve the model's performance by customizing predictions to the complexities of severity levels, resulting in a more specialized tool for medical picture interpretation.

C. DenseNet121

DenseNet, an advanced convolutional neural network design, is well-known for its dense connectivity structure, which encourages feature reuse and efficient information flow. DenseNet, which was trained on the ImageNet dataset, learnt rich hierarchical features from a broad variety of objects and situations. Its convolutional layers are combined into a Sequential model, which is then followed by a Global Average Pooling layer, which condenses the spatial dimensions. Additional layers are incorporated, including a Dense layer with 128 neurons and ReLU activation, to capture additional abstract information important for diabetic retinopathy severity classification, and another dense layer at the end with SoftMax to predict the class. The resultant model, with a total of 7,169,349 parameters, strikes a balance between generalization and task specificity. This fine-tuned architecture, efficient in both compute and memory, serves as a robust tool for accurate predictions.

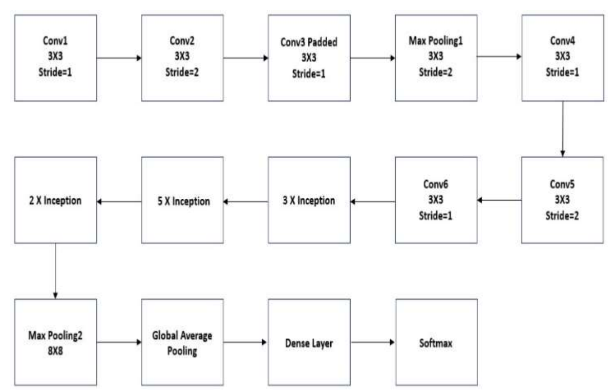

Fig. 4. Proposed architecture of Inceptionv3

D. MobileNetV2

MobileNetV2's convolutional layers are frozen in order to keep the general features learned during ImageNet pretraining. The spatial dimensions are condensed by a Global Average Pooling layer, which is followed by Dense layers (256 and 128 neurons) with ReLU activation, which capture more abstract properties and a final dense layer with SoftMax. The overall amount of parameters is 2,619,461, with 361,477 trainable parameters when the extra layers are included.

V. RESULTS AND ANALYSIS

The performance of multiple deep learning models on the task of diabetic retinopathy severity classification using greyscale retinal pictures is examined in this section. EfficientNetB0, InceptionV3, DenseNet121, and MobileNetV2 are the models under consideration. Prior to modelling, two filters were applied to the dataset separately: the Gaussian filter and the Gabor filter along with greyscale which was present in the original dataset. The best strategy will be determined by comparing models and filters. The filtered datasets were used to train the deep learning models, and test accuracy was used to determine benchmarks. Accuracy was tested independently on the training and test sets for each model-filter combination over numerous trials. The results Table1 displays six accuracy assessments per model, one for each dataset-trial combination.

Model	Greyscale		Gaussian		Gabor	
	Train	Test	Train	Test	Train	Test
EfficientNetB0	90.89%	63.35%	97.68%	81%	97.5%	69.35%
InceptionV3	**98.77%**	**76.61%**	**98.33%**	**84.23%**	**86.9%**	**77.15%**
DenseNet121	82.74%	79.7%	74.14%	76.74%	73.4%	73.6%
MobileNetV2	81.22%	72.64%	77.14%	76.19%	78.76%	77.15%

Table 1. Comparison of Results

Across trials, InceptionV3 outperforms various other models on the Gaussian filtered data, obtaining over 80% test accuracy. We also observed that comparatively, almost all the models reached their peak when trained with Gaussian images. InceptionV3 uses multiple convolutional layers with differing filter sizes to extract features at various scales. Its complex design with the usage of inception modules, which comprise numerous parallel convolutional procedures. This helps to capture both fine and coarse details in retinal pictures.

Gaussian filter is best suited when it comes to classification and prediction of Diabetic Retinopathy. One of the main reasons for this is Gaussian filters are extensively employed in image noise reduction. Since these retinal images contain noise due to lighting conditions or poor-quality photography, the Gaussian filter is be actively smoothing it out and improving the overall image quality. The features enhanced by Gaussian filtering better reflect the particular characteristics of diabetic retinopathy. It was observed that the nerves and nerve endings were better highlighted in the images after applying this filter. These extracted features are more significant for differentiating between the distinct classes. Gabor filter mainly concentrated on contrasting regions on the retina but this did not help the models' effectively capture features. Greyscale images lacked clarity and did not provide good results.

The difference was significant when compared to the other models' 70-80% range. Its superiority, however, is less obvious on Greyscale filtered data, where accuracies are more tightly grouped. InceptionV3 and Densnet121 have reasonably stable filter performance, sitting in the 75-80% ranges. MobileNetV2 and EfficientNetB0, on the other hand, lag with test accuracy ranging from mid-60% to low-70%. It is normal for training and validation losses to first decline as the model learns. It is common for the training loss to decrease over the course of the epochs as the model improves at predicting the training set. But after around five epochs, the validation loss starts to rise again after first declining.

This is a sign of overfitting, a condition in which the model learns too much from the training set, including subtleties and noise that don't transfer to new data. The divergence of the training and validation curves indicate overfitting in Fig. 5 (i). After the first few epochs in Fig. 5 (iii), there is a noticeable divergence between the training and validation losses, which usually indicates overfitting. It's possible that the model is picking up on training data-specific learning patterns that don't translate well to new data.

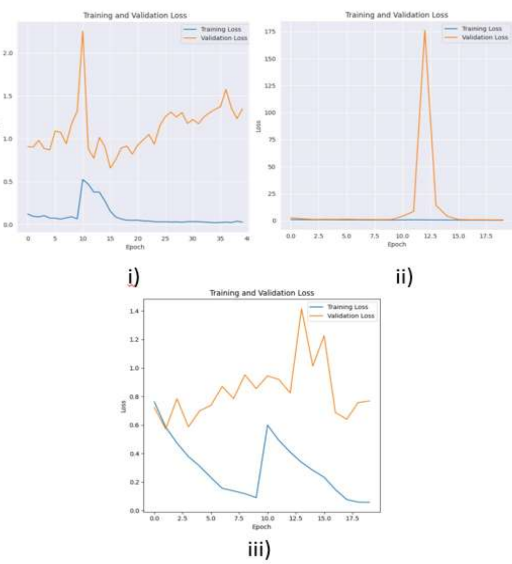

Fig 5. Loss Plots (i) Gaussian (ii) Greyscale (iii) Gabor

VI. CONCLUSION AND FUTURE SCOPE

Given that our paper focuses on the many filters that were applied to the original greyscale photos, the Gaussian filter emerged as the most promising filter among those that were used. This is due to the fact that features improved by Gaussian filtering in conjunction with the InceptionV3 model shown a greater ability to capture the crucial features of diabetic retinopathy. This filter improved the visibility of the blood vessels and nerves in the pictures. The significance of these extracted traits lies in their ability to distinguish between the various classes. The Gabor filter primarily focused on contrasting areas of the retina, although this was ineffective in assisting the models in successfully capturing information.

This paper's work could be expanded upon and improved by using different filters on the initial grey-scaled dataset. Additionally, we have access to a variety of pre-processing methods such as Region of Interest (ROI) trimming and histogram equalization. This may result in an improvement in the blood vessel and nerve visibility, which could raise the model's accuracy for the early detection of diabetic retinopathy. The vision transformer (VIT) is another significant model that might be applied to this dataset because it has been shown to perform better than more conventional deep learning models.

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