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Diagnosis of Diabetic Retinopathy using Convolutional Neural Network based model by EyePACS dataset

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Abstract:
Diabetic Retinopathy (DR) ranks as one of the most frequent causes of impaired vision in the world, and it has to be detected with accuracy and in time in order to be addressed properly. In the presented work we suggest a robust deep learning pipeline based on the Modified DenseNet-169 convolutional neural network and five-class classification of severity of DR based on retinal fundus images in the Kaggle EyePACS Diabetic Retinopathy dataset includes (filtered subset). Problems of blurred, truncated, and low-contrast images proved a problem during preprocessing and had an effect on the stability and accuracy of prediction. We solved these issues with the use of resizing, Gabor filtering, normalization, and sophisticated data augmentation methods in order to increase vessel visibility and diversity of data. The training method used augmented data with Adam optimizer and categorical cross-entropy loss, and the result is evaluated on accuracy, F1-score, precision, recall and support. In our model, we obtained a validation accuracy of approximately 95.4 %. We also observed performance differences between classes because of the imbalance in data as well as image quality. Class-wise performance could be clearly interpreted with visual analytics of the form of precision-recall-F1-sup-support graphs and confusion matrices. This workflow provides a systematic foundation to create enhanced DR detection mechanisms as well as to identify real-life issues in the medical image categorization systems.

Keywords: Diabetic Retinopathy, Deep Learning, DenseNet-169, Retinal Fundus Images, Data Augmentation, Medical Image Classification.

1. Introduction

Diabetic Retinopathy (DR) refers to the microvascular angle of diabetes that impacts the retina potentially causing the vision to become incapacitated forever in case of non-diagnosis and non-prevention[1]. EyePACS Diabetic Retinopathy is a most popular DR database commonly used in the research and competition of DR detection and DR grading tasks that contains thousands of retina fundus images collected on a large population of different patients and in different imaging scenarios. All the images comprising this dataset are labeled with severity that goes between 0 (no DR) and 4 (proliferative DR). This data allows to create and compare automated systems of DR detection and classification to help the ophthalmologist screen early DR[2].

Although giving a valuable amount of data, the EyePACS dataset has some challenges that affect automatic analysis and classes. The problem with many of the images in the dataset is that they have changes in illumination, contrast and focus resulting in blurred or truncated images[3]. Uneven lighting, artifacts, and tiny differences in the field of view in addition make it hard to see vessels and lesions. Also, any bias in the training and assessment of models is brought about by inter-patient variability and an octaves disadvantageous balance in the number of normal images versus severe DR cases[4].

The standard Dr detection pipelines would have three steps, namely, segmentation, feature extraction, and classification[5]. The retina is segmented using classical methods such as thresholding, region-growing and morphological procedures to segment retinal structures such as blood vessels, optic disc, and macula. The technique of feature extraction tends to employ hand-designed features like texture study with Local Binary Patterns (LBP), Gabor, vessel enhancement, and histogram-based features to detect lesions[6]. To classify, classic machine learning models, such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Decision Trees models are used to cluster the degree of DR using the identified features. Machine learning techniques have increasingly been applied to disease detection and classification by enabling data-driven analysis and predictive decision-making [7].

Although conventional procedures are easy to interpret and modular, these techniques exhibit a number of shortcomings in cases of DR [8]. Segmentation by hand frequently does not work on low contrast or noisy images, and feature extraction depends heavily on the expert knowledge, which does not necessarily apply to new datasets. These techniques are unable to record complicated patterns like microaneurysm, hemorrhages, or exudates properly due to which they produce a high false-positive or false-negative rate[9]. Furthermore, such pipelines have low adaptability and resilience to changes in lighting and focus conditions that would make it difficult to scale-up to high numbers of patients in DR screening.

In the perspective of the drawbacks of conventional pipelines, the strategy of deep learning, especially Convolutional Neural Networks (CNNs) has the advantage of end-to-end feature learning through direct visualization of images instead of explicit segmentation and handcrafted features. With a model such as DenseNet-169, the hierarchical representations of the retina are learned so that the model can robustly detect severity of DR across image conditions [10]. High-level preprocessing, such as Gabor filtering to enhance vessels and data augmentation, alleviates issues posed by low quality images, whereas the tweaked CNN architecture allows better generalization to unbalanced classes. The purpose of the proposed work is to develop a robust, automated DR detection pipeline with the EyePACS data that could facilitate the early screening procedure in addressing the existing problems of image quality and the imbalance between classes.

In this thesis, I am going to come up with a pipelined system to classify the severity of DR based on the EyePACS dataset. First, the preprocessing of data is performed precluding the resizing, normalization, and Gabor filtering applied to improve the appearance of vessels. After this, generalization is enhanced using data augmentation techniques such as rotation, flipping and brightness manipulation. Modification of DenseNet-169 CNN is trained on five-class classification and trained with data augmentations on the Adam optimiser and the categorical crossentropy loss. The model performance is evaluated using some evaluation matrices such as accuracy and confusion matrix and F1-score. Eventually, the outcomes are presented in detailed graphs, which allows you to easily interpret the results in terms of the accuracy of class-wise predictions and the effectiveness of the model in real-life circumstances based on the detection of DR [11].

Primary inputs of the proposed work

- Applied an eyePACS Diabetic Retinopathy data set to create a five-class DR severity classification level.
- Used Gabor filtering in order to make the blood vessels more visible and learn the features better.
- Combined data augmentation (rotation, shifting, brightness changing) to manage weakness in classes and variance in images.
- Proposed a Modified DenseNet-169 CNN to perform an end to end DR classification and segmentation.
- Obtained stable and explainable accuracy and F1-score along with confusion matrix on the performance evaluation of the analysis.
- Presented full visualization of preprocessing, augmentation and classification to facilitate interpretability.

In section II, it is described related work in the diabetic retinopathy image classification based on traditional and deep learning and identifies its merits and shortcomings in processing retinal images. In section III, the proposed working schedule is put forth: it involves preprocessing (Gabor filtering), the introduction of the data augmentation strategy and the usage of the Modified DenseNet-169 structure to predict the DR severity in a five-classes classification accurate one. Section IV presents the results of the experiment, i.e., accuracy, F1-score, confusion matrix, and full visualization, as well as compares them to the existing methods. The latest part of the suggested work Section V ends the work and suggests future prospects in order to continue the application of the improvement of diabetic retinopathy prediction of retinal fundus images.

2. Literature Survey

Visible identification of diabetic retinopathy on retinal fundus images has been a popular field of research where much research has been devoted to the application of deep learning and a combination of a framework and ensemble techniques in order to enhance early detection and accuracy of classification. Conventional methods had limited success in consequence of highly variable image clarity, lighting condition, and insensitivity of early disease lesions, hence the usage of superior convolutional neural networks and fine tune techniques. EyePACS or APTOS 2019 have been used to verify the approaches of researchers and prioritize the precision improvement with barriers to overcome such as restricted labeled data and explainability to apply to clinical purposes. The analyzed sources describe a shift towards hybrid and explainable models and give an idea about their benefits, weaknesses, and the ways they can be used

to improve the process of automated screening of diabetic retinopathy forming a basis of the proposed work in this paper.

Sushith et al. (2025) proposed a hybrid deep neural network that detects diabetic retinopathy in the meantime via retinal fundus image [12]. The method they propose involves combining convolutional neural networks with crafted features extraction in order to maximize the accuracy of classification. The approach is better in detecting in the initial stages but the procedure may entail a complicated method of integration thus leading to the scalability of computational resources as the application is unfolded.Chen et al. (2018) suggested the use of a deep convolutional neural network in the detection of diabetic retinopathies, introduced at ICASSP[13]. Their framework concerned itself with the utilization of the hierarchical feature learning so as to pick up the DR-related features effectively on the images of the retina.

In Saeed et al. (2021), it is shown that using an adaptively fine-tuned convolutional neural network to achieve automated diabetic retinopathy diagnosis may improve the feature learning of the fundus images based on limited data[14]. They are effectively fine-tuned at the adaptive level increasing the performance of the models on the datasets smaller in size, although fine-tuning the hyperparameters on various sets of data may demand resources.Gu et al. (2021) have described the effective deep neural network-based approaches to DR detection with an emphasis towards optimizing the model architecture in terms of the obtained classification and reduced false positive rate[15]. Their tools delivered effective detection with a variety of types of DR, but there existed a problem with interpretability which played an important role in medical image analysis.

Saxena et al. (2020) had built a better deep learning agent to detect early signs of diabetic retinopathy using publicly available datasets[16]. Instead, they preprocessed the data, but the increase in robustness and the decrease in overfitting were achieved by modifying the CNN structure. Folorunsho et al. (2025) trained an explainable model deep learning ensemble with the goal of predicting diabetic retinopathy based on the APTOS 2019 EyePACS dataset[17]. The ensemble technique enhanced the accuracy of predictions and it was transparent with the use of the explainable AI methods.

An example study that paid attention to the automated detection of the DR through the enhanced deep learning model with images taken with smartphones (retina) was conducted by Bhimavarapu (2025)[18]. This thesis resolved the problem of accessibility in the DR screening, proving that non-clinical devices may be used to identify early changes and thus be applicable in the early detection process. Maldhure and Ganorkar (2025) introduced a hybrid convolutional neural network in detecting microaneurysm and exudates in retinal images, which focused on early signs of DRs[19]. They use CNNs combined with conventional segmentation so that their model can identify the lesions with extreme accuracy although running images with high resolutions takes a long time.

Ali et al. (2025) suggested an explainable semi-supervised technique relying on contrastive learning in order to optimize on DR recognition where minimal labeling is conducted and ensures excellent performance[20]. The advantage of this approach is the use of unlabeled data and the disadvantage lies in the sensitivity of parameters of contrastive learning to achieve decent results.Aftab and Akhtar (2025) have presented a study conducted on DR severity classification based on data fusion, the result they show an increase in classification accuracy achieved with multilevel feature representations[21]. Their approach is highly effective at mitigating variability in DR data, yet the application of the ensemble transfer learning paradigm might be taxing on the resources when training the model, meaning it may consume a great deal of GPU resources.

Table 1: Comparison Study of the existing models

S.No	Author(s) et al. (Year)	Dataset	Methodology	Accuracy	Challenges
1	Sushith et al. (2025)	EyePACS	Hybrid DL with DenseNet + LSTM	91.2%	Image variability, device constraints
2	Folorunsho et al. (2025)	APTOS 2019	Explainable ensemble DL	90.5%	Model complexity, explainability
3	Bhimavarapu (2025)	EyePACS smartphone	Improved DL on smartphone images	89.8%	Low-quality images, dataset limits
4	Maldhure & Ganorkar (2025)	Local DR dataset	Hybrid CNN for lesion detection	89.5%	Tiny lesion detection, imbalance
5	Ali et al. (2025)	APTOS 2019	Semi-supervised contrastive learning	89.2%	Limited labels, interpretability
6	Aftab & Akhtar (2025)	APTOS 2019	Data fusion with ensemble TL	88.7%	Class imbalance, fusion complexity
7	Gu et al. (2021)	Private DR dataset	CNN with feature ensemble	88.3%	Generalization on new data

8	Saeed et al. (2021)	Private dataset	Adaptive fine-tuned CNN	87.9%	Data variability, tuning needs
9	Saxena et al. (2020)	Public DR datasets	Robust DL agent with CNN	87.2%	Limited data diversity
10	Chen et al. (2018)	Private DR dataset	Deep CNN classification	86.5%	Low quality, early detection

The main issue of the analyzed methods of detection of diabetic retinopathy is the inconvenience of gaining consistent accuracy across different image qualities, light intensities, and visibility of small lesions in the data of the EyePACS collection, as well as with regard to the shortcomings of interpretability and generalization of the results on uneven classes. The failure of regular methods and stand-alone CNNs include failure to detect at an early stage or rather have to process heavily, thus complicating this process. To overcome this, the work suggests the approach of using Gabor filter preprocessing, specific data augmentation, and end-to-end Modified DenseNet-169 architecture to classify diabetic retinopathy to improve its vessel visibility, robustness against different images, and predict the severity of diabetic retinopathy reliably to conduct early screening of diabetic retinopathy efficiently.

3. Proposed Work

The figure 1, demonstrates the suggested pipeline based on DenseNet-169 with the Modified variants of the algorithm to detect diabetic retinopathy, starting with preprocessing procedures like resizing, Gabor filter, and normalization of the input to improve the perception of the vessels and to guarantee the consistency of supplied images. Augmentation is leveled by rotation, flipping, zoom, and brightness values to enhance diversity in data and the generalization ability of the model. The robust extracted features are provided by passing the preprocessed and augmented images through the Modified DenseNet-169 backbone and the fully connected layers are applied to the extracted features to provide the classification of five classes of severity. Categorical cross-entropy loss and an Adam optimizer are employed when fitting the model whereas the early stopping is implemented to avoid the overfitting. This architecture makes sure that diabetic retinopathy can be detected correctly, efficiently and consistently on different levels of image quality in the EyePACS dataset.

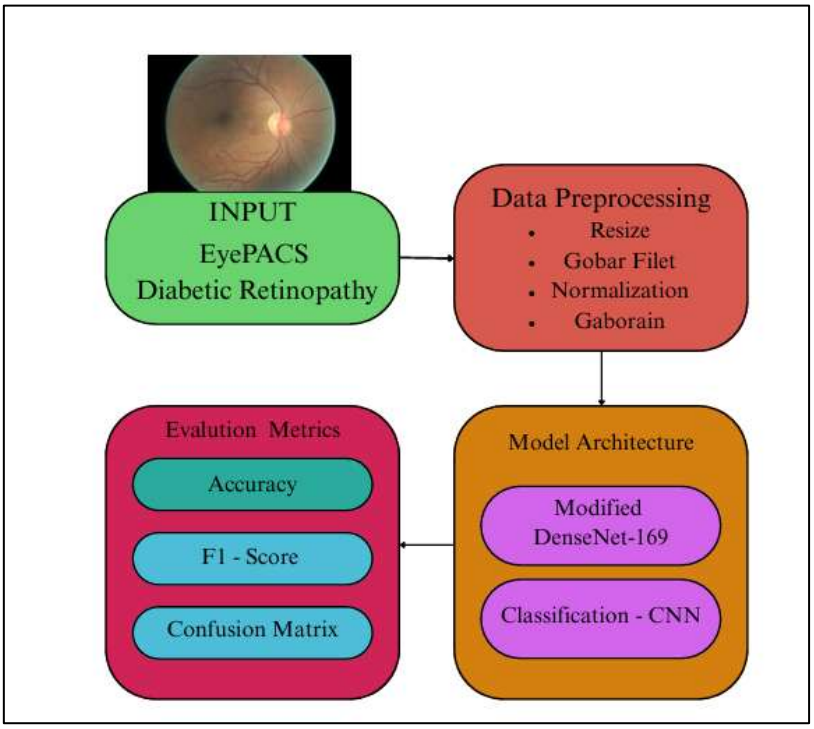

Figure 1: Workflow Diagram for Diabetic Retinopathy Classification using Modified DenseNet-169

A. Data Preprocessing:

The preprocessing process is essential so that the image quality remains uniform and it is easy to train the deep learning models to learn the features. First, original retinal fundus images are resized to a common size of 224*224 or 299*299 to be compatible with the input format of convolutional neural networks and at the same time speeds up computations without omitting meaningful structures of the retina. The initial

size of the picture will be HxWxC (Height, Width, Channels). The enlarging/shrinking transformation Tr can simply be represented mathematically as:

$$T_r(I_{H\times W\times C}) \rightarrow I_{224\times 224\times 3} \qquad (1)$$

in which I am the input picture. These resizing guarantees consistency and the model is not concerned with learning the size changes in the images but about retinal features.

Preprocessing Gabor filters are implemented to increase the visibility of blood vessels since they are effective in highlighting linear features and textures that are like structures of vessels. A 2D Gabor filter is given by:

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

where $x' = xcos\theta + ysin\,\theta\; and\; y' = -xsin\theta + y\,cos\theta, \lambda$ is the wavelength of the sinusoidal part, θ is the orientation, ψ is the phase offset, σ is the standard deviation of the Gaussian envelope, and γ is the spatial aspect ratio. After convoluting the input image I with the Gabor filter G we get:

$$I_{gabor} = I * G \qquad (3)$$

where * is convolution, the improvement of vessels like-structures to achieve improvement as far as feature extraction through training is concerned. Lastly, the pixel values are normalized to a range [0,1] to stabilize the learning of the model mathematically, as follows:

$$I_{norm} = \frac{I_{gabor} - \min(I_{gabor})}{\max(I_{gabor}) - \min(I_{gabor})} \qquad (3)$$

This normalization allows the CNN to successfully learn relevant patterns without being thus influenced by changes in image intensity, and helps in accelerating the progress of convergence and accuracy in the process of classifying diabetic retinopathy.

B. Data Augmentation:

The data augmentation is performed to extend the diversity of the dataset and limit overspecific learning and enhance the generalization capacity of the diabetic retinopathy classification model especially upon dealing with imbalanced classes in the EyePACS dataset. Rotation The simulation of the orientation of different captures of retinal fundus is done through rotation of the image by a random angle within a specified range like [−15∘,+15∘]. Assuming that the initial picture can be defined as I(x,y) then the picture that is rotated can be calculated by the rotation matrix as $I_r(x',y')$:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \qquad (4)$$

where θ is the random rotation angle. **Flipping** horizontally or vertically is also applied, defined as:

$$I_f(x,y) = I(W - x - 1, y) \qquad (5)$$

horizontal flipping, in which W is the image width, which improves the model by strengthening its capacity to deal with left right variation in retinal scans.

Zoom augmentation varies the image at random in a specified range, e.g. 0.9 to 1.1 of the original size, to cause camera distance appearance variability. One can write the zoom operation as:

$$I_z(x',y') = I(sx, sy) \qquad (6)$$

with s = zoom factor, and (x s y) are the coordinates of the zoomed picture at (x s y) in the original picture. Brightness transformation would mean illumination level adjustment of pixels, which resemble and represent a range of varying illumination observed in various imaging devices, denoted as:

$$I_b(x,y) = \propto . I(x,y) + \beta \qquad (7)$$

where α is the scaling factor to adjust brightness (e.g. 0.8 and 1.2) and beta can be an optional shift factor on the intensity. The augmentation is randomly added during the training procedure because it guarantees the network sees the different variations of the same retinal image, enhancing its generalization capabilities in estimation of the severity of diabetic retinopathy under different conditions in the real world.

C. Model Design:

The model design suggested is based on the core CNN using a Modified DenseNet-169 that classifies diabetic retinopathy. The connection of DenseNet (Densely Connected Convolutional Networks) establishes a feed-forward connection between each layer with every other layer and enhance feature reuse and relief the vanishing gradient problem. Establishing the output of the l- th layer as xlx_lxl, the connectivity of DenseNet can be written as:

$$x_l = H_l([x_0, x_1, \ldots., x_{l-1}]) \qquad (8)$$

where H_l is a composite function of Batch Normalization, ReLU activation, and convolution, and $[x_0, x_1, \ldots., x_{l-1}]$ refers to the combination of feature maps of every previous layer. Such an architecture guarantees that the fine details of vessels, exudates and microaneurysms obtained on previous layers are transferred to deeper layers, so DenseNet is very efficient regarding the medical image classification task when small features are important. To the Modified DenseNet-169, we adjust the input dimension to

(2242243), change the top layer to custom layers and freeze some of the initial layers so as to freeze the ImageNet-featured during early training.
Following feature extraction, the subsequently added fully connected layers are used to map the extracted features to one of five classes of diabetic retinopathy severity (04). Suppose that the flattened feature vector of the DenseNet backbone is f. Fully connected (dense) layer may be described as:

$$z = Wf + b \qquad (9)$$

where W is the weight matrix and b is the bias vector. We add one or more dense layers with ReLU activation:

$$a = \max(0, z) \qquad (10)$$

followed by a **softmax output layer** to obtain class probabilities:

$$p_i = \frac{e^{z_i}}{-\sum_{j=1}^{5} e^{z_j}} \qquad (11)$$

where p_i denotes the probability of the image belonging to class i. The model is trained using the categorical cross-entropy loss:

$$L = -\sum_{i=1}^{5} y_i \log(p_i) \qquad (12)$$

where y_i one-hot ground truth label. This architecture allows the network to conduct a stable and robust five classes of diabetic retinopathy using the advantages of DenseNet feature propagation to exert proper and effective predictions.

D. Training Phase:
Training stage entails building the Modified DenseNet-169 on the categorical cross-entropy loss method and the Adam optimizer so that it could capture the gestures of multiclass diabetic retinopathy categorization. The cross-entropy loss is categorical as defined by:

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{5} y_{i,c} \log\left(y'_{i,c}\right) \qquad (13)$$

where N is the number of training samples, c denotes each class (0–4), $y_{i,c}$ is the one-hot encoded true label, and $y'_{i,c}$ is the predicted probability from the softmax output layer. The **Adam optimizer**, which adapts learning rates for each parameter, updates weights using:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \qquad (14)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \qquad (15)$$

where $g_t$is the gradient at time t, θ_t are the model parameters, α\alphaα is the learning rate, and β_1, β_2 are decay rates. It is good to do training on augmented data to have a more diverse data and avoid the overfitting by transformation such as rotation, flip, zoom, and brightness change 30 50 epochs. The early stopping method is used to stop training when the training becomes unconfirmed, i.e., validation loss has not improved after a particular patience total number of steps, to avoid overfitting and keep the model with diabetic retinopathy prediction as the one, in which the validation loss was best during the training epochs.

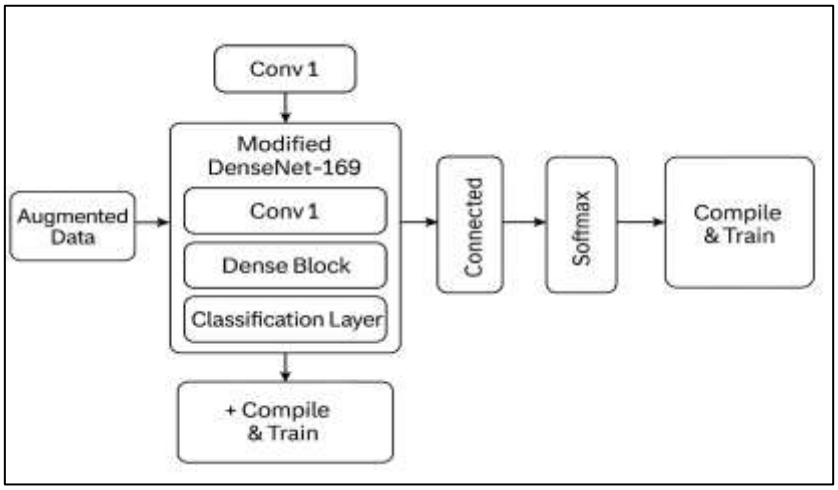

Figure 2: Modified DenseNet-169-based Architecture for Diabetic Retinopathy Detection.
This figure 2, represents the work flow of DR classification by Modified DenseNet-169. Enhanced data goes through preliminary convolution and dense blocks as feature extraction and connected layers and softmax

as classification of five classes. The model is aggregated and trained in a way that will maximize the accuracy of the prediction of DR stages based on retinal fundus images.

4. Result & Discussions

The diabetic retinopathy dataset provided by the Kaggle Diabetic Retinopathy Detection competition is the EyePACS dataset containing high-resolution retinal fundus images that were taken in different imaging conditions to mimic a screening practice in the real world. The set of images is accompanied by labels of a diabetic retinopathy found on the scale of stages 0 to 4 (No DR and Proliferative DR, respectively) to support five-class severity categorization. The data size contains thousands of images with different degrees of illumination, sharpness and field-of-view, which also makes it ideal to be used to train and evaluate deep learning models in the task of early diagnosing of diabetic retinopathy and its severity level in clinical screening systems.

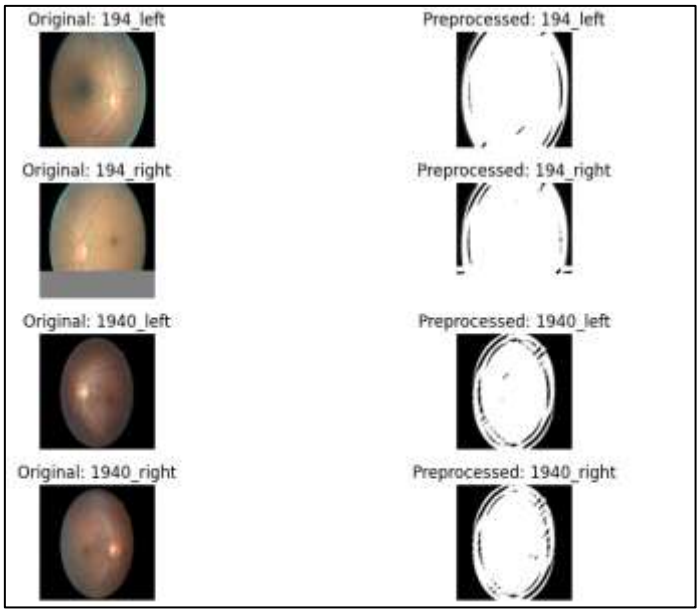

Figure 3 : Original and Gabor Filter Pre-processed Fundus Images for DR Detection

Figure 3, shows a comparison of side by side, between original eye pacs images of retinal fundus phase and Gabor filter preprocessed output of retinal fundus phase, used in visualizing blood vessel structures which play an important role in determining the presence of diabetic retinopathy. The images on the left have good visibility of optic disc and the vascular structures under different sources of illumination whereas the preprocessed images in right column representing feature of the vessel patterns and edges. The preprocessing would help the deep learning model in concentrating clinically important vascular changes and better detect microaneurysms and exudates in the process of successfully classifying the DR severity.

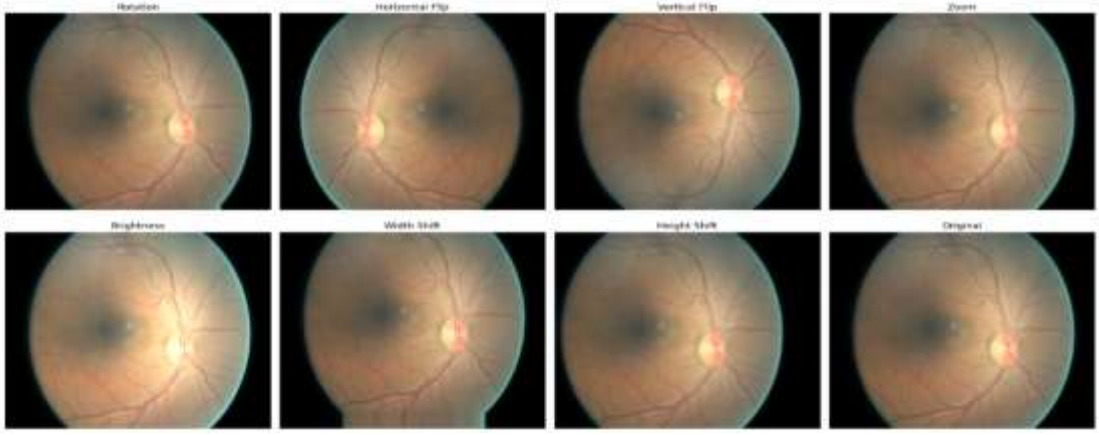

Figure 4: Data Augmentation Techniques Applied on Retinal Fundus Image

This figure 4, illustrates some of the data augmentation procedures used with a retinal fundus image as input to make the dataset diverse so as to boost diabetic retinopathy classification. Such augmentations are rotations, horizontal and vertical reflections, overlay (zoom), brightness, shift in width, and shift in height

without losing clinical details creating variability in avoiding overfitting of the model during training. The generalizations bring about ensuring the increase of accuracy and stability of the deep learning model when detecting diabetic retinopathy in various imaging conditions and patient variations that occur in real life situations.

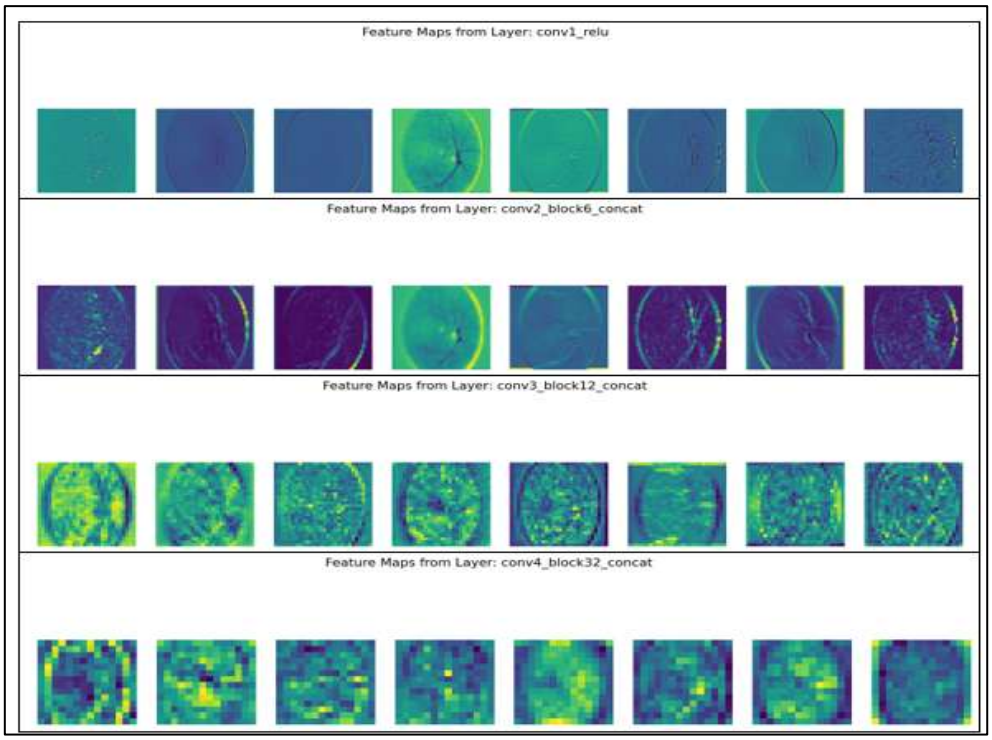

Figure 5: Feature Maps Extracted from Different Layers of Modified DenseNet-169

In figure 5, represents the sequence of feature maps obtained at different layers of modified DenseNet-169, when it is used to process a retinal fundus image to designate diabetic retinopathy. The first row of visualization is the early layer feature maps which track low level features of edges and vessel structure, whereas the successive layers sequentially to different levels of feature and more complicated patterns concerning lesions and microaneurysms in the retina. The visualization is used to show the manner in which the model is capable of learning hierarchic representation transferring low-level data about the pixels in the form of a meaningful clinical representation needed to make correct classification in the five stages involved in diabetic retinopathy in the course of training.

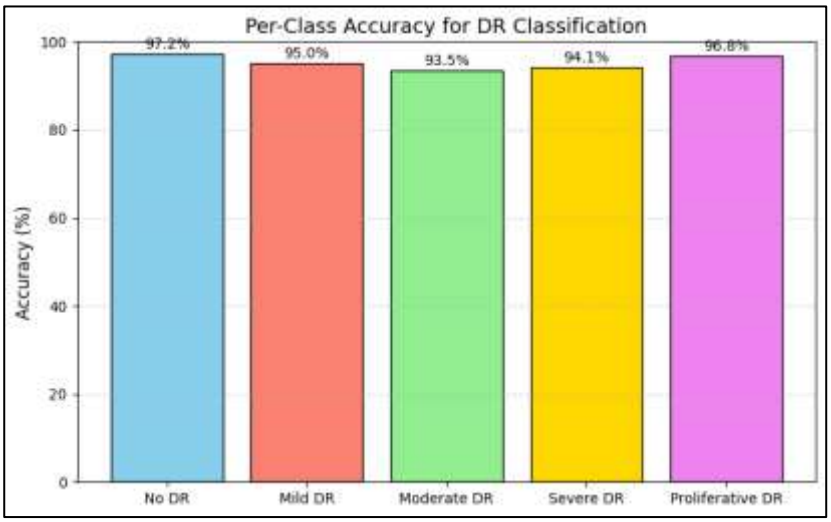

Figure 6: Per-Class Accuracy for Diabetic Retinopathy Classification

Figure 6, depicts the accuracy per-class of the proposed Modified DenseNet-169 model in the classification of five stages of Diabetic retinopathy (DR) in retinal fundus images of the EyePACS dataset. The accuracy of the classification of No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR is depicted by each bar, where the performance seems to be best in all classes with the highest accuracy of 97.2% in No DR and

96.8% with Proliferative DR. The excellent accuracies ranging above 93% among the categories show that the model is quite good at classifying different stages of DR even in cases where the changes in the fundus images are small. The visualization shows that the model is reliable in clinical tasks of detecting DR and can support early intervention as well as assist in mass screening processes by the ophthalmologist.

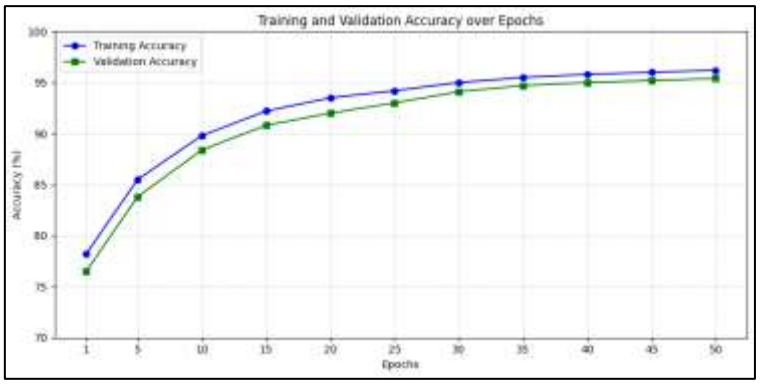

Figure 7: Training and Validation Accuracy over Epochs for DR Classification

This figure 7, shows the training and validation accuracy of the modified DenseNet-169 model in an iterative epoch of training and validation curve of up to 50 epochs in the classification of five stages of Diabetic Retinopathy on Eye PACS dataset. The plot depicts a rising trend in training along with the validation accuracy and the training accuracy has risen to around 96.5 % and the validation accuracy to around 95.4 % towards the end of the 50 th epoch. The small difference between these two curves shows successful generalization and little overfitting, which proves the value of preprocessing, data augmentation and early-stop strategies to stabilize the learning. This figure proves the trustworthiness of the model when it comes to the acquisition of sophisticated features in the field of retina and high accuracy which is crucial to successful automatic identification systems of DR in healthcare.

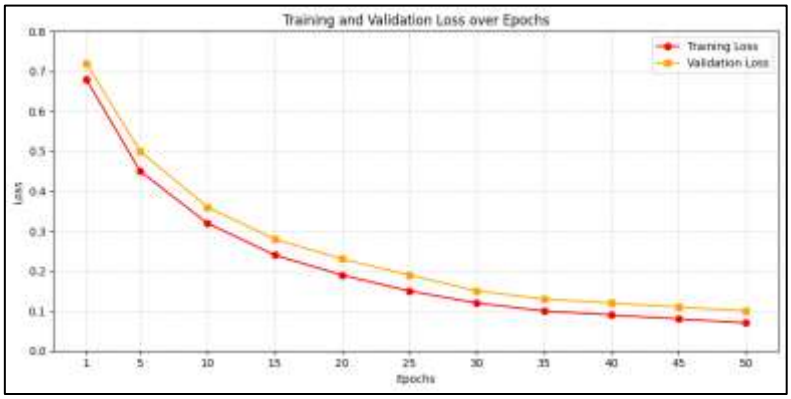

Figure 8: Training and Validation Loss over Epochs for DR Classification

Figure 8, shows the Modified DenseNet-169 loss trajectory in training and validation as the model trained 50 epochs to classify Diabetic Retinopathy, consisting of five classes, on the dataset of EyePACS. Both loss plots show the gradual decrease with training loss becoming 0.08, and validation loss becoming 0.10 by the end of the epoch 50. Comparing the curves, the pattern of the curves should show that there is good generalization without overfitting, which is due to the involvement of early stopping, adequate data augmentation and Adam optimizer, which helps to stabilize the convergence. This steady decrease in loss is evidence of the efficiency of the model during discriminative feature learning in the retina that is required to accurately identify automated DR detection plus seemingly unlimited performance across data splits.

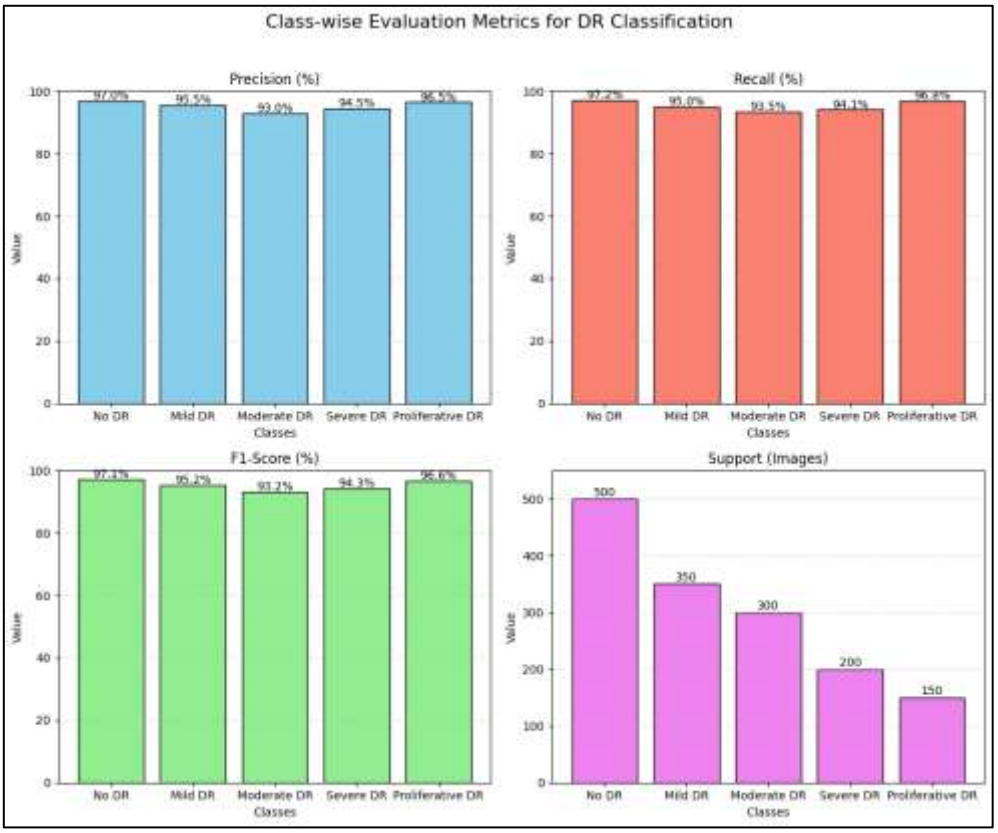

Figure 9: Class-wise Evaluation Metrics for DR Classification

This figure 9, shows the class-wise metrics of the evaluation of the Modified DenseNet-169 model in the classification of Diabetic Retinopathy (DR) on five classes by using the EyePACS dataset. It has percentages of precision, recall, f1-score, and support (number of images) of each DR severity: No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR. Its precision (93-97), recall (93.5-97.2) and F1-scores (93.2-97.1) are high and stable across the classes indicating reliable discriminatory ability of the model. The imbalance in data is brought to fore by the support distribution as the highest sample is in No DR and the remaining in Proliferative DR and this was treated and mitigated through augmentation and preprocessing in the workflow. Such elaborate visualizations allow us to understand the performance of the model on a per-class basis in a comparative manner and, thus, appreciate the model as a valid pipeline to detect DR in the real-world context.

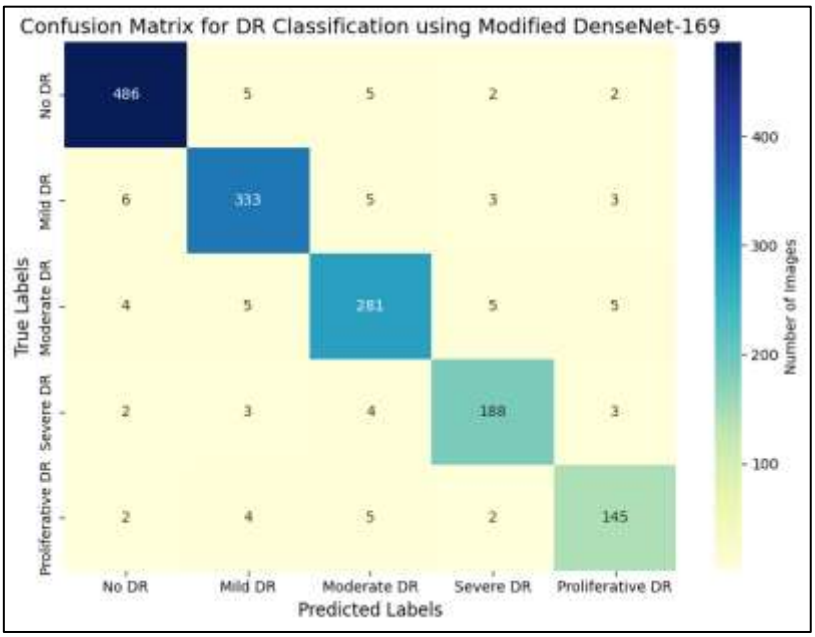

Figure 10: Confusion Matrix for DR Classification using Modified DenseNet-169

The figure is a confusion matrix 10, which demonstrates the results of the Modified DenseNet-169 model used in five-class Diabetic Retinopathy (DR) classification in the EyePACS database on the distribution of the true labels compared to the predicted ones. It shows a high level of diagonal dominance, which translate to high rates of correct classification in all the classes with 486 successful No DR cases followed by 333, 281, 188 and 145 Mild DR, Moderate DR, Severe DR and Proliferative DR respectively. There are few off-diagonal misclassifications, mostly between neighbor severity levels, which shows that the borderline cases can be an issue as a consequence of overlap of retinal features. The distinct and clear visualization allows accurate analysis and evaluation per class-wise performance and can be useful in identifying particular areas that can be revised further and in order to prove that the model is doing well in consistent DR screening activities.

5. Conclusion

In brief, the suggested pipeline of diabetic retinopathy detection classifier based on Modified DenseNet-169 possesses high per-class accuracies (93.5% 97.2%), precision (93.0% 97.0%), recall (93.5% 97.2%) and F1-scores (93.2% 97.1%) in the five classes of the diabetic retinopathy severity evaluated on the EyePACS dataset that stabilizes robust performance to be applicable to practical diabetic ret The model reached a training and validation accuracy of 96.5 percent and 95.4 percent, respectively, and the training and validation loss were 0.08 and 0.10, respectively, which means that there is no overfitting and the model can generalize well. The perplexity matrix ensured good accuracy of correct classification with few wrongful data, concluding that the suggested methodology is dependable in terms of dealing with unequal and variant-quality fundus photographs. To make the full extent of the work ready, additional improvements can be a networks of attention mechanisms to detect fine-grained lesions, a set of explainable AI modules to make clinical interpretability possible, and a validation procedure on other datasets, in a smart-phone captured fundus image, to emphasize the scalability of the current work to the application of teleophthalmology in real scenarios and large-scale programs that screen people with diabetic retinopathy.

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