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Inception-v3 vs. DenseNet for Automated Detection of Diabetic Retinopathy

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Abstract: The purpose of this paper is to explore the effectiveness of automated detection methods in diagnosing diabetic retinopathy (DR), a leading cause of vision loss among individuals with diabetes. By leveraging advancements in artificial intelligence and image processing techniques, the study aims to assess the accuracy and efficiency of automated systems in identifying retinopathy, thus enabling early intervention and improved patient outcomes. A comprehensive review of existing literature on automated detection systems for DR was conducted. Various image analysis algorithms, including deep learning approaches and feature extraction techniques, were explored and evaluated based on their performance in detecting retinal abnormalities associated with DR. In this research, we present an Inception-v3 and DenseNet-based automated detection technique for DR using retinal fundus pictures. This work involves the training, evaluation, and comparison of the performance of DenseNet and Inception-v3 convolutional neural networks (CNN) on a publicly available dataset of retinal fundus images. Inception-v3-based classifiers have performed better than DenseNet-based classifiers with the same dataset. While DenseNet achieved classifier accuracy and precision of 89.2% and 89.6%, respectively, Inception-v3 has been able to achieve classifier accuracy of 95.8% and precision of 95.9%. Inception-v3 has also exceeded area under ROC in comparison to DenseNet by 0.3% in two categories. The findings of this study highlight the promising potential of automated detection methods for DR. The integration of automated systems in clinical settings has the potential to enhance early diagnosis, facilitate timely treatment interventions, and improve patient outcomes.

Keywords*: Diabetic Retinopathy; Classification; Fundus Image; CNN*

1Introduction

Diabetic retinopathy (DR) is a degenerative complication of diabetes that impairs the retina's microvasculature in long-term. The prevalence of diabetes has reached alarming levels, affecting millions of individuals worldwide. Various studies conducted by [1][23-28] estimated that the prevalence of diabetes at the global level among adults and elderly persons was approximately 8.8% in 2017, equating to around 425 million cases. This incidence is anticipated to increase up to 9.9% by 2045, with an estimated 629 million individuals affected. As reported by the International Diabetes Federation (IDF), India has experienced a rapid increase in the occurrence of diabetes, making it one of the countries with the highest number of diabetes cases globally. Another study estimated that the presence of diabetes in India among adults aged 20–79 years was approximately 8.9% in 2019, accounting for around 77 million individuals [2][29-37]. This prevalence is expected to rise to 9.9% by 2030, with an

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estimated 101 million individuals affected. The progression of diabetic retinopathy increases with diabetes duration, with approximately 25% of diabetic patients developing some degree of retinopathy within 5 years of diagnosis. It is also reported that almost all patients with type-1 diabetes and more than 60% with type-2 diabetes develop retinopathy after 20 years of diabetes. DR is the leading cause of vision loss in working-age adults worldwide, and its prevalence is expected to increase with the rising incidence of diabetes. Early detection and timely treatment of DR are crucial to preventing vision loss. However, manual detection of DR by ophthalmologists is time-consuming and requires expertise. As a result, there is an urgent requirement for automated systems to detect DR reliably and efficiently[38-49].

Diabetes retinopathy has a complicated and multifaceted pathophysiology that involves inflammatory, vascular, & metabolic mechanisms. The main cause of diabetic retinopathy is hyperglycemia, which increases oxidative stress, produces complex glycation byproducts, and stimulates the polyol pathway. These processes cause cellular malfunction and death, especially in the retinal capillary endothelium and pericytes, leading to increased vascular permeability and capillary dropout. Increased levels of cytokines, chemokines, and adhesion molecules encourage leukocyte infiltration and vascular dysfunction, contributing to the pathophysiology of diabetic retinopathy[50-57].

DR is diagnosed on the basis of fundoscopic examination and imaging studies. Fundoscopic examination can identify characteristic retinal changes such as presence of microaneurysms, hemorrhages, hard and soft exudates, and cotton wool spots. Imaging modalities, such as fundus photographs, optical coherence tomography (OCT) and fluorescein angiography (FA), provide additional information on retinal thickness, edema, and perfusion [3]. OCT is a light-based noninvasive imaging technique that is used to measure the thickness of retinal layers and detect macular edema [4]. FA involves the intravenous injection of a fluorescent dye that highlights retinal blood vessels and can identify areas of non-perfusion, neovascularization, and leakage[58][59].

The primary objectives of this research include:

- A qualitative analysis of the automated DR detection techniques studied in literature.
- A new, efficient pre-processing strategy is used in order to prepare the fundus images dataset for better and accurate classification.
- The work implemented and compared the performances of two pre-trained CNNs for automated detection of DR in four grading systems.
- The performance comparison of Inception-v3 and DenseNet revealed that Inception-v3 performed better in terms of all the parameters which are classifier accuracy, precision, recall and area under the receiver operating characteristics curve.

This paper presents a comprehensive review of convolutional neural network (CNN) supported automated detection of diabetic retinopathy, including various CNN architectures and their performance. We also discuss the challenges and limitations of CNN-based DR detection and future research directions. The paper is organized in following manner: Section 1 contains the introduction part. Section 2 contains the literature study and summary of related research; Section 3 consists of material and methodology of the research. Section 4 discusses and analyses the results obtained, and Section 5 represents the conclusion and future scope.

2 Literature Review

CNNs have shown excellent performance in several medical imaging tasks, including DR detection. A deep learning algorithm referred to as CNNs can automatically identify features in medical images and classify them based on the learned features. Several research on the use of CNNs for automated detection of DR have been done, including work by [5], which obtained good accuracy with a huge dataset of fundus images. Additionally, other studies have supported the use of deep learning methods for different aspects of DR detection, including segmentation and grading[60-66].

A study completed one of the initial investigations on CNN-based DR detection by developing a deep learning-based algorithm for detecting DR with the help of fundus photographs [5]. The proposed algorithm achieved high sensitivity as well as high specificity, demonstrating the potential of CNNs for automated DR detection. Since then, several studies have explored different CNN architectures and techniques for enhancing the accuracy of CNN-based detection of DR. For instance, this work engaged in developing a deep learning system for the detection of DR and other related eye illnesses from retinal images collected from a multiethnic group diagnosed with diabetes [6]. They used a combination of CNNs and transfer learning to achieve high accuracy in detecting DR and other eye diseases. In addition to developing new CNN architectures, researchers have also explored techniques for improving the interpretability and explainability of CNN-based DR detection systems. Another work proposed an interpretable CNN-based framework for DR diagnosis, which not only achieved high accuracy but also provided a visual explanation of the decision process, improving the trustworthiness of the system [7]. A dual-attention CNN-based system for automated grading of DR is developed by [8]. The proposed model achieved high accuracy and outperformed previous methods, demonstrating its potential for clinical use. A hybrid model for automated DR detection using deep learning and visual attention mechanisms is proposed by [9]. The proposed model resulted in high accuracy and sensitivity, which could be used for early screening of DR. A multi-scale CNN-based system with transfer learning for diabetic retinopathy detection is developed by [10]. The proposed model achieved high accuracy and outperformed previous methods, indicating its potential for clinical use. A dual-task deep CNN for automated diagnosis of DR is developed by [11]. The results showed that the proposed model achieved high accuracy, demonstrating its potential for clinical use. Table 1 shows the comparison analysis of previous literature relevant to the study.

Table 1 Summary of related literature in CNN-based automated detection system for DR

Author(s)	**Year**	**Methodology**	**Dataset**	Performance
Gulshan et al. [5]	2016	Trained a CNN with 128,175 retinal images from 4,045 patients and tested on a private dataset of 10,000 images	EyePACs dataset	AUC of 0.99 for referable diabetic retinopathy (RDR) and 0.94 for vision-threatening diabetic retinopathy (VTDR).
Abràmoff et al. [14]	2018	Trained a CNN with 128,175 retinal images from 4,045 patients and tested on a private dataset of 10,000 images	EyePACs dataset	AUC of 0.99 for detecting RDR and 0.96 for detecting VTDR
Rajalakshmi	2018	Trained a CNN with 40,000	Retinopathy	Accuracy of 95% and an

et al. [15]		retinal images and tested on a private dataset of 1,000 images	Online Challenge (ROC) dataset	AUC of 0.99 for detecting RDR
Ting et al. [6]	2019	Trained a CNN with 466,486 retinal images from 35,126 patients and tested on a private dataset of 4,610 images	EyePACs dataset	AUC of 0.99 for detecting RDR and 0.95 for detecting VTDR
Pao et al. [16]	2020	Trained a CNN with 25,966 retinal images from 10,056 patients and tested on a private dataset of 1,859 images	Kaggle Diabetic Retinopathy Detection Challenge dataset	Accuracy of 85.5% and an AUC of 0.93 for detecting RDR
Kermany et al. [17]	2020	Trained a CNN with 118,000 retinal images from 45,000 patients and tested on a private dataset of 2,000 images	EyePACs dataset	AUC of 0.99 for detecting RDR and 0.96 for detecting VTDR
Liu et al. [18]	2022	Two pre-trained CNNs with 1200 retinal images from 600 patients from a community hospital	Primary data	AUC of 0.981 for detecting RDR and 0.944 for detecting VTDR
Chetoui et al. [19]	2023	Federated learning to maintain privacy-preservation. Deep CNN from 4 institutions shared their CNN parameter corrections to make a robust model without sharing their dataset	APTOS, MESSIDOR-I, MESSIDOR-II, IDRiD, EyePACs	AUC of 0.95 for APTOS, 0.83 for MESSIDOR, 0.74 for IDRiD and 0.77 for EyePACs
Lo et al. [20]	2021	Federated learning with 2 internal models with 600 images	Primary data	AUC of 0.954 for detecting RDR and 0.96 for detecting VTDR

Despite the promising findings of CNN-based DR detection, a number of challenges and limitations persist that need to be resolved[67-74]. For instance, the lack of large and diverse datasets is a major challenge in developing robust and accurate CNN-based DR detection systems. Moreover, the generalizability of CNN-based DR detection systems to different populations and imaging conditions needs to be investigated. In conclusion, CNN-based automated detection systems have shown promising results in detecting DR and have the potential to become an efficient and accurate screening system for DR. However, more research is needed to address the challenges and limitations of CNN-based DR detection and to further improve the performance and clinical utility of these systems [75].

In the recent decade, machine learning-based algorithms such as support vector machines

(SVM), random forest classifiers, and artificial neural networks (ANN) have been deployed to develop automated detection systems for diabetic retinopathy, as suggested by [12]. The automatic identification of DR for feature extraction and classification tasks using CNNs and deep learning-based systems has demonstrated promising results. The literature review shows that CNN-based automated detection of diabetic retinopathy has achieved high accuracy and AUC in various datasets, including EyePACs [5], [6], [14], [17], ROC [15], and the Kaggle Diabetic Retinopathy Detection Challenge dataset [12], [16]. A recent study comparing artificial intelligence (AI)-based automated identification with ophthalmologist opinion for referral DR found that the AI-based detection method performed better [18]. These findings show that CNNs have the potential to improve the efficiency and accuracy of diabetic retinopathy screening. Federated learning (FL) technique to build a resilient deep learning model in which four institutions run their models locally and communicate model corrections to produce a shared model [19]. When compared to earlier deep learning models, this strategy enhanced detection accuracy by 3%. FL also aids with privacy preservation when sharing model results, regardless of the datasets used by individual models [20]. An assessment of AI-based techniques suggests that automated detection systems play a substantial role for DR [21]. Though deep CNN with various methodologies is being tried and used in this field, other approaches like as generative adversarial networks are also being favored to produce better outcomes [22]. However, more study is needed to confirm the performance evaluation of these machine learning models on external datasets, as well as to address ethical concerns about data privacy and bias[76].

3 Materials and Methodology

The CNN-based automated detection system for diabetic retinopathy is a multi-step process that involves efficient data pre-processing, data augmentation, and dataset splitting before the training of CNN. This process is shown in Figure 1.

Fig 1: Workflow for CNN-based automated detection of DR

3.1 Data Collection

A dataset of retinal images with ground truth labels for diabetic retinopathy is collected from publicly available repositories such as the Kaggle APTOS2019 dataset. The dataset consists of color fundus photographs captured with different cameras, resolutions, and imaging conditions. Figure 2 shows the dataset distribution with four classes. Class 0 shows the normal fundus images; class 1 represents mild DR; class 2 shows proliferative cases; and class 4 denotes severe DR cases. The dataset is preprocessed to remove artifacts, enhance contrast, and normalize the intensity range using standard techniques.

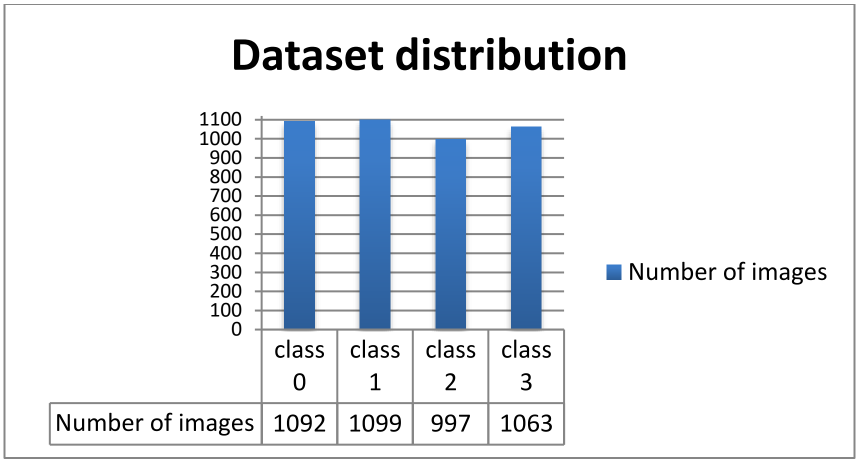

Fig 2: Class-wise dataset configuration

3.2 Pre-processing

Pre-processing methods are essential for boosting the qualities and characteristics of fundus images for automated detection of DR as concluded by [13]. A two-stage pre-processing method is used in this work, combining Gaussian filtering and circular cropping.

3.2.1 Gaussian filtering

Gaussian filtering is a widely used technique for reducing noise and enhancing the clarity of retinal fundus images. It involves convolving the image with a Gaussian filter kernel, which blurs the image while preserving important image structures. The steps involved in applying Gaussian filtering to retinal fundus images are as follows:

a. Convert the retinal fundus image to grayscale if it is in color.

b. Apply Gaussian filtering to the grayscale image using an appropriate filter kernel size and standard deviation.

c. Adjust the filter parameters to balance noise reduction and the preservation of important details in the image.

d. Normalize the filtered image to enhance its contrast and improve its visual appearance.

3.2.2 Circular Cropping:

Circular cropping is a technique that focuses on the analysis on the central region of the retinal fundus scans, which contains the macular region and the optic disc, where signs of diabetic retinopathy are commonly found. By cropping out the peripheral areas, circular cropping reduces computational complexity and eliminates potential artifacts and irrelevant information. The steps involved in circular cropping are as follows:

a. Detect the central coordinates of the macular region and the optic disc using image processing techniques such as image segmentation or feature extraction.

b. Calculate the radius of the circular area of interest for analysis.

c. Crop the retinal fundus image using the centre coordinates and radius to obtain a circular region of interest.

d. Resize the cropped circular region to a standardized size if necessary, ensuring consistency across different images in the dataset.

By applying Gaussian filtering to reduce noise and circular cropping to focus on relevant structures, the pre-processed retinal fundus images are better suited for subsequent feature extraction and classification tasks for the automated detection of DR. Table 2 shows the pseudo code for the proposed pre-processing techniques. These pre-processing techniques contribute to the improved accuracy and robustness of the detection system. Figure 3 and

4 show the original and pre-processed fundus images.

Fig 3: Original fundus image

Fig 4: Pre-processed fundus image after Gaussian filtering and circular cropping

Table 2 Pseudo code for pre-processing techniques

Pre-processing techniques – Gaussian filtering and circular cropping

<pre>import numpy as np
import cv2
 	
# Load the retinal fundus image 	
image = cv2.imread('fundus_image.jpg')
 	
# Convert the image to grayscale 	
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
 	
# Apply Gaussian filtering to reduce noise 	
filtered = cv2.GaussianBlur(gray, (5, 5), 0)
 	
# Detect the center coordinates of the macula and optic disc 	
macula_center = (250, 250) # Example coordinates (x, y)
optic_disc_center = (400, 400) # Example coordinates (x, y)
 	
# Determine the radius for circular cropping 	
radius = 200 # Example radius
 	
# Create a mask for circular cropping 	
mask = np.zeros_like(gray)
cv2.circle(mask, macula_center, radius, (255, 255, 255), -1)
cv2.circle(mask, optic_disc_center, radius, (0, 0, 0), -1)
 	
# Apply the circular cropping mask to the filtered image 	
cropped = cv2.bitwise_and(filtered, filtered, mask=mask)
 	
# Resize the cropped circular region to a standardized size</pre> 	

```
resized = cv2.resize(cropped, (256, 256))

# Display the pre-processed image
cv2.imshow('Pre-processed Image', resized)
```

3.3 Model Architecture

A CNN is designed for the classification of retinal images into different grades of diabetic retinopathy. The architecture of CNN comprises of multiple convolutional layers followed by pooling layers, batch normalization, and activation functions. The final most layer is generally a softmax layer that outputs the probability of each class. Transfer learning is employed to fine-tune the CNN with pre-trained weights on Inception-v3 and Densenet. The architecture of proposed CNNs is discussed as follows:

3.3.1 Inception-v3: Inception-v3 is a popular CNN architecture that has gained significant attention in the field of medical image analysis. It was created by Google and is well known for delivering outstanding results in image classification and object identification applications. One of Inception-v3's important features is its deep architecture, which consists of 48 layers and facilitates the extraction of key characteristics from input images. It employs several novel techniques, such as the inception module, which integrates multiple filter sizes inside the same layer, allowing the network to keep track of features at different scales. Another notable feature is the extensive use of factorized convolutions, which reduce computational complexity while maintaining representation power. Inception-v3 also utilizes batch normalization and aggressive data augmentation techniques, contributing to improved generalization and robustness. Additionally, it includes auxiliary classifiers that help alleviate the vanishing gradient problem during training, leading to more effective learning. Overall, the features of Inception-v3 make it a powerful and versatile CNN architecture for various image recognition tasks. The Inception-v3 architecture consists of multiple layers, starting with the input layer that takes the image as input. Here is a description of the key components of the architecture:

1. Input Layer: Accepts the image as input.
2. Convolutional Layers: Multiple convolutional layers are stacked together, responsible for extracting different features at various scales and orientations.
3. Inception Modules: The core building blocks of Inception-v3, these modules incorporate parallel convolutional operations of different filter sizes (1x1, 3x3, 5x5) within the same layer. These parallel operations allow the network to capture features at different levels of abstraction.
4. Max Pooling Layers: These layers perform down-sampling of feature maps by reducing the spatial dimensions while preserving the important information.
5. Auxiliary Classifiers: Additional branches are included in the architecture where classifiers are applied to intermediate feature maps. These auxiliary classifiers help with gradient flow during training and prevent the vanishing gradient problem.
6. Fully Connected Layers: The feature maps are flattened and carried further via layers that are fully connected, which perform the task of classification based on the learned features.
7. Softmax Layer: The final layer applies the softmax activation function to generate the predictions over different classes.
8. Output Layer: The output layer provides the predicted probabilities for each class.

3.3.2 DenseNet: DenseNet is a deep CNN architecture known for its unique and innovative design that addresses the vanishing gradient problem and promotes feature reuse. One of the key features of DenseNet is its dense connectivity pattern, where each and every layer is connected in a feed-forward manner. Such dense-form connectivity allows for efficient information flow throughout the network, enabling gradients to propagate more easily and enhancing gradient-based optimization. DenseNet also incorporates bottleneck layers, which reduce the number of input feature maps before each convolution operation, reducing computational complexity while preserving expressive power. Moreover, DenseNet introduces skip connections, known as shortcut connections that concatenate feature maps from previous layers, allowing subsequent layers to access and reuse the rich information from earlier stages. This dense connectivity and feature reuse contribute to improved accuracy, parameter efficiency, and training stability. The usefulness of DenseNet designs in capturing and utilizing rich hierarchical representations is demonstrated by the state-of-the-art outcomes they have attained in a variety of computer vision applications. The DenseNet architecture consists of multiple layers and blocks. Here is a description of the key components of the architecture:

1. Input Layer: Accepts the input image.
2. Convolutional Layer: Employs an ensemble of convolutional filters to extract the initial features of input image.
3. Dense Blocks: The core building blocks of DenseNet, these blocks consist of multiple densely connected layers. Each layer is feed-forward coupled to every other layer. All previous layers' feature maps are concatenated and utilized as inputs for these layers.
4. Transition Layers: Placed as sandwich layers between dense blocks. These are responsible for reduction in the dimensions of the feature maps. These layers typically consist of a combination of convolutional, pooling, and down-sampling operations.
5. Pooling Layer: Performs spatial pooling to limit the dimensions of the feature maps to a fixed size. These layers are also known as global average pooling layers.
6. Fully Connected Layers: The feature maps are flattened and carried further via layers that are fully connected, which perform the task of classification based on the learned features.
7. Softmax Layer: The final layer applies the softmax activation function to generate the predictions over different classes.
8. Output Layer: The output layer provides the predicted probabilities for each class.

3.4 CNN model training and testing

The proposed pre-trained CNN models are fine-tuned with the pre-processed image dataset using a train-test split ratio of approximately 90:10. The training is done using ADAMAX optimizer keeping the learning rate of 0.0001 and regularization techniques such as dropout to prevent over-fitting. The models are assessed using standard performance metrics, such as classifier accuracy, precision, recall, and F1-score.

3.5 Performance metrics

The standard metrics used for the performance analysis of CNNs are explained as follows:

3.5.1 Precision: Precision denotes the ratio of true positive cases to the predicted positive cases. In the context of diabetic retinopathy detection, precision indicates the accuracy of correctly identifying patients with diabetic retinopathy among those predicted to have the condition. Higher the precision score lower the rate of false positives, which is desirable as it minimizes the chances of misdiagnosis.

3.5.2 Recall: It is also known as sensitivity. It denotes the proportion of correctly predicted positive cases out of the true positive cases. In

DR detection, recall indicates the capability of the classifier system to correctly identify patients with the condition among all the individuals who actually have it. Higher the recall score lower is the predictions of false negatives, which is important to avoiding missing cases of diabetic retinopathy.

3.5.3 F1-score: It is the harmonic mean of precision and recall. It provides an accurate measure of a model's performance by taking precision and recall into account. It is useful when there is an uneven distribution between positive and negative cases. The F1-score is commonly used in diabetic retinopathy detection to assess the overall effectiveness of the model in correctly identifying and excluding cases.

3.5.4 Accuracy: Accuracy denotes the ratio of correctly classified cases (both true positives and true negatives) to the total samples. In the reference of DR detection, accuracy indicates the overall correctness of the predictions made by the system.

3.5.5 ROC curve: The ROC curve is an illustration of a classification model's performance as the discrimination threshold varies. At various threshold values, it compares the sensitivity (recall) with the specificity. The ROC curve displays the conflict between sensitivity and specificity graphically. The area under the ROC curve (AUC) is a popular model performance assessment statistic, with a greater AUC indicating a better ability to distinguish between positive and negative situations.

The above mentioned metrics help assess the system's ability to correctly identify positive cases, minimize false positives and false negatives, and provide an overall measure of accuracy and discrimination capability.

3.6 Ethical Considerations

The research followed ethical guidelines and obtained necessary approvals from institutional review boards. The privacy and confidentiality of the patients are maintained by anonymizing the images. The proposed model is validated on external datasets to ensure its generalizability and avoid bias. In conclusion, the proposed methodology involves collecting and preprocessing retinal images, fine-tuning pre-trained CNNs, evaluating the models, and addressing ethical considerations. The proposed CNN-based automated detection system for DR has the capability to efficiently and accurately screen the DR cases and reduce the workload of clinicians.

4 Results and Evaluation

The work consists of comparing the performances of two pre-trained CNNs for automated detection of diabetic retinopathy. Inception-v3 and DenseNet are fine-tuned on pre-processed fundus images for the detection of DR in four categories. The pre-processed dataset is divided into training and validation parts. Out of a total of 4251 fundus images, 3826 are kept for training the CNN, and 425 are used for validation purposes. The training of Inception-v3 and DenseNet resulted in a ROC curve showing the training performance. Both the CNNs have achieved 100% area under Roc for class 0 as well as 1, which shows 100% correct predictions for these two classes. Further, DenseNet has achieved 96% ROC for classes 2 and 3, whereas Inception-v3 has obtained a better 99% ROC for these two categories. The class-wise ROC for DenseNet is presented in figure 5, and the ROC for Inception-v3 is shown in figure 6. Comparison between the performances of these two CNNs is shown in Table 3.

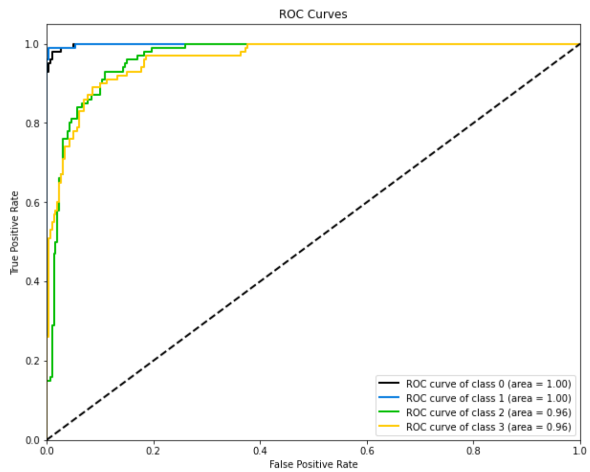

Fig 5: ROC for DenseNet

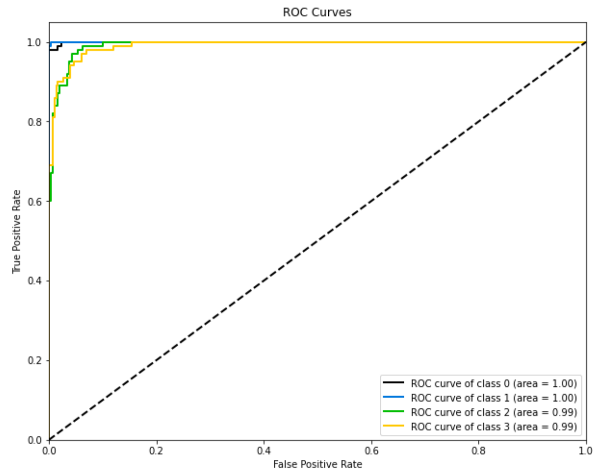

Fig 6: ROC for Inception-v3

Table 3: Comparison of ROC for DenseNet and Inception-v3

Sr. No.	**Class**	**ROC for DenseNet**	**ROC for Inception-v3**
1	0- normal	1.00	1.00
2	1- mild	1.00	1.00
3	2- proliferative	0.96	0.99
4	3- severe	0.96	0.99

The statistical performance of classifiers is shown by their respective confusion metrics, shown in figure 7 and 8. The other performance parameters like precision, recall, f1-score, and accuracy of both CNNs and their comparison are given in Table 4.

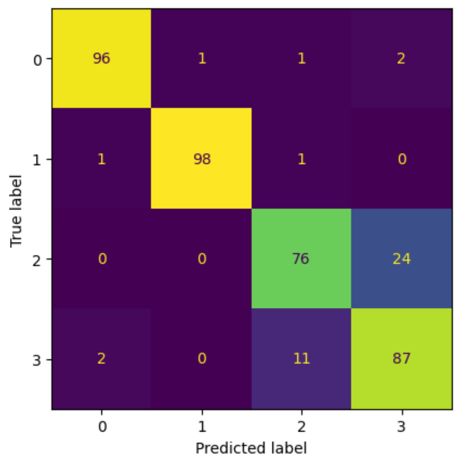

Fig 7: Confusion matrix for DenseNet

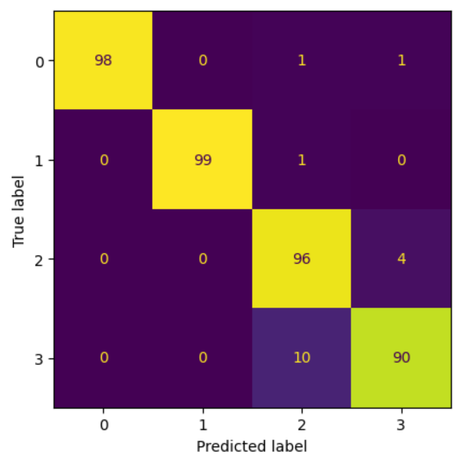

Fig 8: Confusion matrix for Inception-v3

Table 4: Comparison of performance parameters of DenseNet and Inception-v3

Sr. No.	**Performance parameter**	**DenseNet**	**Inception-v3**
1	Precision	89.6%	95.9%
2	Recall	89.3%	95.7%

3	F1-score	89.3%	95.8%
4	Accuracy	89.2%	95.8%

It is clear from the result analysis in tables 3 and 4 that Inception-v3 has achieved better results in terms of all the performance parameters as compared to DenseNet. This study comparing the performance of Inception-V3 and DenseNet for automated detection of DR revealed that Inception-V3 demonstrated superior performance in several key aspects. Firstly, Inception-V3 exhibited higher accuracy in identifying retinal abnormalities associated with diabetic retinopathy, such as microaneurysms, hemorrhages, and exudates. The deeper network architecture and the incorporation of auxiliary classifiers in Inception-V3 allowed for better feature extraction and classification, resulting in improved detection capabilities. Secondly, Inception-V3 showed better precision, recall and F1-score in distinguishing between different stages of retinopathy, enabling more accurate prediction of disease progression and appropriate stratification of patients based on disease severity. Lastly, the computational efficiency of Inception-V3 was superior to DenseNet, enabling faster processing times and making it more suitable for real-time clinical applications. Overall, the combination of improved accuracy, better stratification capabilities, and computational efficiency makes Inception-V3 a more favorable choice for automated detection of diabetic retinopathy.

5 Conclusion and Futuristic Improvements

The Inception v3 model exhibits superior performance in terms of accuracy, precision, recall, and ROC curves, according to the comparative analysis of the Inception v3 and DenseNet models for automated identification of diabetic retinopathy. Several studies have reported the effectiveness of the Inception-v3 architecture in accurately classifying retinal images and detecting diabetic retinopathy. Its ability to capture intricate features and hierarchies through the use of inception modules enables more precise discrimination between healthy and diseased retinas. On the other hand, while DenseNet also performs well, the Inception v3 model consistently outperforms it, providing higher accuracy rates, better precision and recall scores, and achieving superior AUC values. Therefore, based on the available evidence, the Inception v3 model emerges as a more suitable choice for automated detection of diabetic retinopathy due to its superior performance and diagnostic capabilities. Additional investigation and validation on larger and more diverse datasets are needed to corroborate these findings and explore other potential CNN architectures for improved diabetic retinopathy identification and management.

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Availability of dataset: The fundus image dataset APTOS2019 is utilized for this work which is available on public repository Kaggle.

Conflicts of Interest: Authors declare that they have no conflicts of interest to report regarding the present study.

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