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Automated Detection of Diabetic Retinopathy: A Comparative Study of Machine Learning Algorithms

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Abstract
Diabetic Retinopathy (DR) is a disorder of the eye and refers to the damage to the blood vessels of the retina as a result of high blood sugar levels in the body. This condition is the most common cause of blindness among working-age people. Vision impairment may result from DR and is regarded as a serious diabetes complication all over the globe. This paper evaluates the efficacy of two deep learning models, DenseNet-121 and ResNet-50, which have a widespread application in performing automated analysis of retinal images and detecting the presence of DR. DenseNet utilizes dense connectivity in order to efficiently reuse features, while ResNet uses residual connections to enhance the training of deep networks. The experiments were conducted on both models using an open-sourced DR dataset and their performance was evaluated with respect to accuracy, sensitivity, specificity and computational efficiency. The results of the analysis suggest that DenseNet is superior to ResNet in terms of accuracy and parameter efficiency, and therefore it is the best method in dealing with DR in a clinical setting. This information may assist the physicians in determining the appropriate models which should be employed for diabetic retinopathy detection in clinics.
Keywords: *Diabetic Retinopathy (DR); Retinal Fundus Image; Deep Learning; Feature Reuse; Residual Connections.*

1. Introduction
Diabetic Retinopathy (DR) is an eye disease which is identified as the damages made in the retina's blood vessels of a diabetic person. Untreated cases of Diabetic Retinopathy can lead to blindness. According to the World Health Organization (WHO), DR is the most common eye disease which is widespread across the globe, 422 million people have diabetes and as such many at risk for a future case of DR. Identifying the disease in its early stages is critical minding the current rise of cases of diabetes all over the globe. Chronic hyperglycemia is the cause of Diabetic Retinopathy, consisting of damages made in the diameter of blood vessels located on the retina [1]. These types of symptoms may cause the emergence of microaneurysms, the existence of blood clots or some tissues, and formation of blood vessels at abnormal locations. DR includes five stages of its progression:

- No DR (Healthy): Basically, no sign of retinal damage, DR is not present.
- Mild DR: Small bumps in the microscopic blood vessels, the starting point of DR.
- Moderate DR: More microaneurysms and bleeding.
- Severe DR: Further disease progression with bleeding and swelling of the retina.
- Proliferative DR: Growth of new and poorly positioned blood vessels that can lead to blindness when they break, shown in Figure 1.

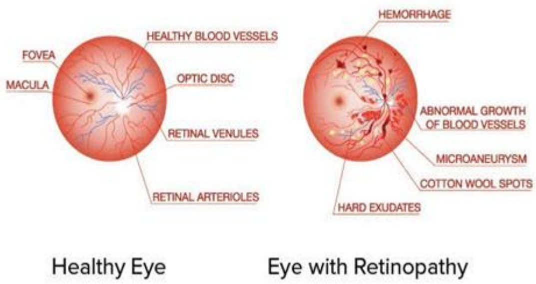

Figure 1 Normal and Affected Retina

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Currently, traditional methods of DR detection utilize the manual analysis of the retinal fundus images by ophthalmologists, which is tedious, subjective and limited by the number of practitioners available. Also, there is a steadily increasing world incidence of diabetic patients as well which enforces the demand for large scale, effective and dependable automated systems for aiding DR diagnosis. Computer-Aided Diagnosis (CAD) incorporating deep learning technologies have been booming in this respect. These deep learning technologies are a branch of artificial intelligence (AI) that interacts with medical images in unprecedented ways. And like, Convolutional Neural Networks (CNN) in particular are achieving quite a high classification performance due to the ability of these layers to learn complex structures in images. In fact, the detection of DR is also gaining significance due to advances in two CNN architectures: ResNet and DenseNet. ResNet: Mitigated the vanishing gradient phenomenon by employing residual blocks, which avails a network to assimilate multiple layers, shown in Figure 2 [2].

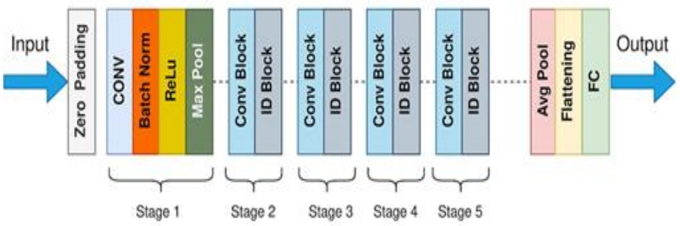

Figure 2 ResNet Architecture

Dense Convolutional Networks (DenseNet): Enhanced internal connections to facilitate feature flow and reuse while creating efficient, compact models, shown in Figure 3.

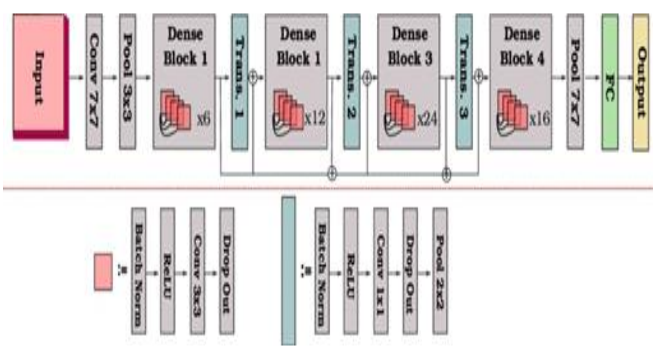

Figure 3 DenseNet Architecture

1.1. Objective

This study's objective is to perform a comparative analysis of ResNet and DenseNet architectures for diabetic retinopathy (DR) detection using retinal fundus images collected from Kaggle. The objectives also include classification accuracy, precision and recall as well as the F1-score in regard to the classification of DR into 5 levels, and the assessment of their training time with respect to DR feature localization that will be evaluated using Grad-CAM. The study aims to inform the development of DR detection optimized models by automated means by exploring both the strengths and the weaknesses of existing models so that they will be useful for diagnosing as well as large-scale screening in low-resource countries for early detection and treatment.

2. Materials and Method

This study employs a comparative approach between ResNet and DenseNet architectures for the detection of diabetic retinopathy (DR) using retinal fundus image [3-7].

2.1. Dataset

We made use of the APTOS Blindness Detection Dataset, composed of 3662 retinal fundus images annotated into one of the following categories:

- No DR (0): The retina appears to be healthy.
- Mild DR (1): The patient has some microaneurysms.
- Moderate DR (2): More microaneurysms and some signs of early hemorrhage.
- Severe DR (3): There are significant lesions such as hemorrhages, and soft exudates.
- Proliferative DR PDR (4): The retina is severely damaged with neovascularization.
- The dataset was divided as follows: Training Set: 80% (2,930 images) Testing Set: 20% (732 images) [8]

2.2. Data Preprocessing

A number of auxiliary activities were carried out as part of the data preprocessing phase to maintain a uniform quality of the images so that efficient training of the model could be achieved. The image contrast was enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE). With this technique, lighting imbalances were equalized as well as visibility of several features of the retina, for

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example, microaneurysms and hemorrhages, enhanced. To provide ResNet and DenseNet models with appropriate input size, all images were resized to 224 * 224 pixels. To reduce overfitting and increase generalizability of the model, the following augmentation techniques were applied:

- Horizontal and Vertical Flipping
- Random Rotation (up to 30 degrees)
- Scaling (Zoom-in and Zoom-out)
- Brightness Adjustment

Pixel values were normalized to a range of 0 to 1. Mean and standard deviation normalization was applied to standardize image inputs [9-13].

2.3. Model Architectures

ResNet and DenseNet deep-learning architectures were deployed in this study. ResNet is a new design that adds residual connections to networks to address the vanishing gradient problem and makes it possible to train deeper networks. There are identity connections in each block that span one or more layers to guarantee feature reuse and improved gradient flow. The choice was resnet-50, because it seems to have a good performance versus a cost ratio. DenseNet also strengthens feature reuse and minimizes unnecessary computations through dense connectivity. Layers pass their outputs to all subsequent layers and receive inputs from every single preceding layer. The concatenation of feature maps in dense blocks of the network is used instead of sum to allow for more efficient feature reuse. The number of features that are added at any layer has a limit that is set by the growth rate (k). DenseNet-121 specifies a growth rate of 32, shown in Table 1.

Table 1 Comparison of Architectures

Feature	ResNet	DenseNet
Connectivity	Residual (skip) connections	Dense (all-to-all) connections
Gradient Flow	Alleviates vanishing gradients	Strong gradient flow due to dense connections
Model Size	Larger	Smaller
Feature Reuse	Moderate	High

2.4.Training Procedure

Both architectures' training procedure comprised the following processes:

1. **Input Preparation:** The prepared images were presented to the models in mini-batches consisting of 32 images (batch size = 32).
2. **Loss Functions:** Categorical cross-entropy loss was applied in ResNet to minimize classification errors, while in DenseNet, maximum probability cross-entropy loss (MPCE) was used which facilitated faster convergence and improved class discrimination for better prediction.
3. **Optimization:** The Adam Optimizer because of its learning rate adaptivity and fast speed was optimized. Learning rate: 0.001 Weight decay: 0.0001
4. **Regularization:** Twenty percent of the neurons were randomly omitted over the periods of training. The training was stopped when the validation loss did improve over the last 10 epochs.
5. **Federated Learning Simulation (DenseNet Only):** This problem of data privacy was solved by training DenseNet in a federated learning scheme. The central model initialized the parameters; and then corded them to client devices (simulated hospitals). Each of the clients focused on locally updating the model with its data portion only. The central server implemented the updates using the federated averaging algorithm.

2.5. Evaluation Metrics

As a complete evaluation of the model performance, the following parameters were calculated:

1. **Accuracy:** The ratio of images that were precisely classified. Accuracy = (TP+TN)/(TP+TN+FP + FN)
2. **Precision:** The ratio of true positives to all of the predicted positives. Precision: TP/ (TP + FP)
3. **Recall:** The ratio of true positives to all of the actual positives. Recall: TP/ (TP + FN)
4. **F1-Score:** The average of precision and recall where the two become interdependent. F1-Score =2*(Precision * Recall)/(Precision +

Recall)

5. **Confusion Matrix:** Each class was assessed independently from the model to derive class metrics.
6. **Computational Efficiency:** Memory and training time were collected for the two architectures.

2.6. Visualization

As a fusion approach to interpret the models' decisions, Grad-CAM Visualization was used to determine viable regions in fundus images. For instance, microaneurysms and hemorrhages were highlighted in site which is paramount for DR identification [14].

3. Result and Discussion

Table 2 Quantitative Results

Metric	ResNet	DenseNet
Accuracy	85%	95%
Precision	83%	89.5%
Recall	84%	90.5%
F1-Score	83.5%	89%
Training Time	Longer (due to deeper layers)	Shorter (efficient feature reuse)

Table 3 Class-wise Accuracy Comparison

DR Class	ResNet Accuracy (%)	DenseNet Accuracy (%)
No DR	92%	98%
Mild DR	75%	86.5%
Moderate DR	82%	95%
Severe DR	70%	89%
Proliferative DR	65%	84.5%

3.1. Class-wise Comparison

A confusion matrix analysis was performed to assess the performance of the models over the five DR severity levels. ResNet had a hard time with high severity cases such as Proliferative DR because of inadequacy in the reuse of features and often misclassified the mild DR cases as no DR. However, DenseNet was able to maintain consistent performance across all classes and was able to successfully identify important features like microaneurysms and hemorrhages. Grad-CAM visualizations once again explained that DenseNet was able to better identify DR features than ResNet and also had a stronger overall performance in classifying the features, shown in Table 2 & Table 3.

3.2. Computational Efficiency

ResNet, owing to its deeper residual connections, has a high computational requirement and training time, especially for large datasets. On the other hand, DenseNet enhances the reuse of features, reduces the parameters, and allows for quick convergence. Grad-CAM's visualizations indicated that ResNet did not seem to effectively locate the major retinal lesions, but DenseNet was capable of detecting microaneurysms, exudates, and hemorrhages that are the hallmarks of DR in its early stages. In many ways, DenseNet outperformed ResNet during all assessment procedures especially with respect to the severe and proliferative stages of Diabetic retinopathy. The performance of ResNet in No DR and Mild DR was good but most challenges were on the severe cases due to the feature extraction constraints.

Conclusion

Diabetic Retinopathy (DR) is a severe consequence of diabetes that can render individuals forever blind if it's not detected and treated at an early point. The automated systems utilizing deep learning algorithms offer great promise for the improvement of DR diagnosis as they are able to dramatically improve the speed, accuracy and scalability of diagnosis compared to conventional manual screening practices. The focus of this study was to test and compare two advanced Deep Learning models, ResNet and DenseNet, for the classification of diabetic retinopathy and its stages using fundus images. The performance of ResNet was outdone by DenseNet as the accuracy of the model was more than 95% while ResNet delivered an overall accuracy of 85%. Additionally, in order to detect severe and proliferative late stages of DR that require early treatment, which included better overall precision, recall and f1-scores, DenseNet was also superior and recorded excellent performance. Further, Grad-CAM visualizations confirmed that DenseNet was more effective in identifying the microaneurysms and

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hemorrhages, hence it was better at diagnosing low DR. Furthermore, DenseNet achieved lower computational burden and quicker training convergence owing to its compact model size and effective feature reuse, thus making it more practical for real life use. Both models were able to show promising performance but had challenges in classifying the imbalanced datasets, especially the minority and rare DR stages. This demonstrates the necessity of balanced datasets or more sophisticated data augmentation methods in subsequent studies.

Implications and Future Directions

The results show that DenseNet can be automatically employed for diabetic retinopathy (DR) detection and therefore, can be easily used in clinical settings. With its increased precision and reduced computational requirements, it is also suitable for large population screening even in poor areas. Furthermore, using federated learning can optimize the performance of the model without compromising the privacy of the data for each institution, in addition to the fact that DenseNet can be incorporated with ResNet in hybrid models to enjoy the strengths of both architectures. It would also enhance generalizability to extend the research to different populations and imaging conditions. In conclusion, there is encouraging evidence for earlier DR detection using DenseNet that could result in timely management and better patient care [15].

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