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A Deep Learning System for Early Diabetic Retinopathy Diagnosis

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Diabetic Retinopathy emerges as a significant etiological factor in global vision impairment among individuals with diabetes. Characterized as a microvascular pathology affecting the retina, it results in vessel obstructions and consequent deprivation of essential nutrients to retinal tissues. Diabetic retinopathy represents a significant complication arising from diabetes mellitus, with the potential to result in visual impairment and eventual blindness if timely diagnosis and intervention are not administered. Manual examination of retinal images by ophthalmologists has been the traditional approach for Diabetic retinopathy detection. The emergence of deep learning has unequivocally transformed numerous domains, and medical image analysis and classification stand as exemplars of this paradigm shift. However, with the growing need for efficient and accessible diagnostics, this research introduces an innovative deep learning-based approach designed for the automated identification of Diabetic Retinopathy (DR). The proposed system depicts an improved performance, evidenced by the highest classification accuracy of 84.1%.
Keywords: Diabetic Retinopathy, Machine Learning, Visual impairments, blindness.

1. Introduction

Detecting diabetes-related diseases promptly and providing precise diagnoses are pivotal in optimizing treatment outcomes and enhancing healthcare delivery. Diabetes, a metabolic dysfunction identified by heightened levels of glucose in the bloodstream, stands as a formidable health challenge with profound implications for diverse organ systems within the human body. On a global scale, approximately 27.0% of individuals with a diabetes diagnosis are estimated to experience diabetic retinopathy, leading to around 0.4 million cases of blindness globally [1]. Diabetic retinopathy is acknowledged as a leading global cause of irreversible blindness and stands as the primary factor contributing to vision impairment among adults during their working years. 80% of those diagnosed with type 2 diabetes are expected to get affected with retinopathy [2]. The retina is a crucial organ that absorbs light and sends information to the brain. Diabetic retinopathy primarily damages this organ. The retina is vascularized, much like other body tissues are, and high blood glucose levels in the context of diabetes can cause damage and alteration of retinal blood vessels, resulting in fluid leakage [3]. Diabetic retinopathy progresses through distinct stages, each characterized by specific changes in the retina. The stages are typically categorized into mild NDPR, Moderate NPDR, severe NPDR, and PDR. It is important to note that the severity of diabetic retinopathy is often graded based on the findings from a comprehensive eye examination. During the screening procedure, certain eye drops make the patient's pupil dilatation easier. This enables the ophthalmologist to use advanced lighting techniques and specialist lenses to inspect the retina comprehensively. It is imperative to acknowledge that to furnish precise and reliable diagnostic outcomes, this approach necessitates specific expertise and experience. With the evolution of healthcare technologies, computer-aided diagnosis systems have evolved as a pivotal advancement for the quick and efficient diagnosis of diverse diseases, among them diabetic retinopathy. Notably, in the context of cost-effective and comprehensive screening analysis, deep learning (DL) models have garnered considerable attention and validation through multiple studies [4], establishing themselves as highly effective solutions for addressing the intricate challenges associated with DR classification. The next part of the chapter discusses the existing work in diabetic retinopathy.

2. Literature Survey

Sudha et al. [5] proposed an approach for diabetic retinopathy detection involving preprocessing input images through resizing and noise filtering, followed by feature selection and extraction. The CNN architecture undergoes training with augmented data, and its performance is evaluated using binary cross entropy, avoiding significant overfitting or underfitting concerns. The model achieves 95% accuracy in testing, indicating its effectiveness. Kangrok Oh et al. [6] presented a system to recognize diabetic retinopathy in its early stages, utilizing ultra-wide-field fundus images. The proposed methodology involves preprocessing the input through Automatic Segmentation of the ETDRS 7SF, facilitating extensive data cleaning. The system adopts ResNet-34 for binary classification, utilizing a relatively modest dataset.

The ImageNet is used to pre-train the ResNet-34 model and fine-tune it in-house to suit the specific requirements of diabetic retinopathy detection. Wejdan L. Alyoubi et al. [7] conducted a comprehensive analysis comparing the performance of deep learning algorithms—CNN, VGGNet, ResNet, and AlexNet—primarily emphasizing metrics such as accuracy, sensitivity, and specificity. Their objective was to leverage deep learning to classify diabetic retinopathy (DR) lesions automatically. The study employed diverse classification strategies, including vessel-based, binary, multi-level, and lesion-based classifications. Through systematic testing using various methodologies, the research highlights the effectiveness of Convolutional Neural Networks (CNNs) in achieving efficient results for DR lesion detection and classification. Supriya Mishra et al. [8] conducted research with a primary focus on detecting (DR) using DenseNet, achieving a notable accuracy of 0.9611 on a dataset comprising 3662 fundus images. The literature review provided in-depth insights into the criticality of DR and conducted a comparative analysis of various CNN architectures, highlighting the superior performance of DenseNet121. The study extensively explored prior research on DR image classification, encompassing discussions on algorithms, transfer learning, and advanced architectures. By contributing valuable insights into DR detection, the research aids in selecting and evaluating Deep Learning models for enhanced diagnostic outcomes. Anas Bilal et al. [9] introduced a unique hybrid approach for classifying the disease, surpassing the performance of previous studies. To bolster reliability, the methodology integrates three classifiers—KNN, SVM, and BT—alongside a collaborative voting mechanism. This innovative system amalgamates preprocessing algorithms, feature extraction techniques, and classification models, yielding notable outcomes with a 95.39% accuracy, 94.98% sensitivity, and 96.27% specificity. Incorporating preprocessing techniques is underscored for its pivotal role in lesion detection, ultimately enhancing overall accuracy. This research provides a comprehensive and promising framework for diabetic retinopathy detection and classification. Dr. G.U. Kharat et al. [10] present a novel approach involving a multi-layer perceptron Neural Network (MLPNN) for diabetic retinopathy detection through the analysis of retinal images. By incorporating a feature vector based on statistical parameters, the MLPNN attains an impressive 98% accuracy in training and testing datasets. The research explores optimal parameters, encompassing 11 hidden Processing Elements, a momentum learning rule, tanh transfer function, and a step size of 0.1. The system showcases elevated sensitivity and specificity, underscoring its efficacy in diabetic retinopathy detection and exhibiting potential for streamlined, automated mass screening processes.

The study conducted by Kh Tohidul Islam et al. [11] focuses on using deep learning to detect diabetic retinopathy using OCT images. The proposed methodology, centered around DenseNet-201 combined with Artificial Neural Networks (ANN), demonstrates superior performance compared to existing approaches regarding accuracy and training time. The findings reveal that the implemented approach achieves a notable accuracy rate of 77.9% and an impressive specificity of 92.6%. This surpasses the performance of other methods, highlighting the superiority of the DenseNet-201+ANN combination in terms of efficiency and diagnostic capabilities.

In this proposed model by Israa Odeh et al. [12], a robust solution for automated diabetic retinopathy (DR) detection is introduced through an ensemble-based architecture. The model employs specific features selected via feature selection algorithms, feeding them into an ensemble framework. The system aims to enhance prediction accuracy by utilizing widely recognized classification algorithms such as Random Forest, Neural Network, and Support Vector Machine (SVM). In the final stage, a Meta-classifier merges the outputs of all algorithms to generate the conclusive prediction. The model, leveraging MESSIDOR's pre-extracted features and avoiding image processing, demonstrates commendable accuracy, as highlighted in the detailed evaluation process.

The survey by Norah Asiri et al. [13] investigates the segmentation of retinal blood vessels and the detection of optic disc features in diabetic retinopathy. Low contrast, morphological changes, and diseases present challenges. Numerous deep learning techniques, like Stacked Autoencoders, Recurrent Neural Networks and Convolutional Neural Networks, have been used. SAE-based techniques perform well, especially when using two-level ensemble structures and cross-modality transformation. The survey also explores optic disc feature detection, where reliable segmentation is achieved using CNNs and SAEs. Evaluation metrics provide essential information for identifying diabetic retinopathy by highlighting the advantages of various models across a range of datasets.

Cheena Mohanty et al. [14] study focuses on early diabetic retinopathy (DR) detection using deep learning models—a hybrid network of XGBoost DenseNet 121. This model leverages VGG16's feature extraction and XGBoost's classification prowess, achieving a 79.50% accuracy. Meanwhile, DenseNet 121 impressively attains a 97.30% accuracy. The evaluation of the APTOS 2019 Kaggle Dataset addresses class imbalance. The comparative analysis highlights DenseNet 121's superior efficacy. The research emphasizes the potential of deep learning architectures, particularly DenseNet 121, in significantly enhancing efficiency and accuracy in DR diagnosis, offering substantial benefits to healthcare providers and patients.

Sumit Thorat et al. [15] conducted a study addressing the detection of (DR). This research proposes an automated methodology employing a Deep CNN trained on a dataset comprising 35,126 retinal images. The CNN model achieves a commendable accuracy of 81%, mitigating the need for extensive manual examination by ophthalmologists. Early identification of advanced stages of DR, which can lead to blindness, poses a significant challenge. The introduced CNN model, leveraging Deep Learning techniques, stands as a promising automated solution, offering potential benefits to patients and healthcare practitioners in effectively managing the disease.

3. METHOD

The existing research landscape on diabetic retinopathy presents notable gaps warranting further exploration. One critical gap pertains to the dataset size utilized in studies, where the scope often remains limited. Expanding the dataset size could offer a more comprehensive representation of diverse cases, thereby enhancing the generalizability of the findings.

A considerable research gap lies in the predominantly binary classification approach adopted in diabetic retinopathy studies. Many existing models focus solely on distinguishing between diabetic retinopathy's presence and absence, neglecting the potential nuances associated with multi-class classification. Incorporating multi-class classification could provide a more nuanced understanding of disease progression, allowing for finer-grained diagnostic categorizations.

Furthermore, the pursuit of high accuracy remains a persistent challenge. While accuracy is crucial, achieving consistently high accuracy levels in diabetic retinopathy detection is often an area of improvement. Addressing this gap involves exploring innovative deep-learning architectures, refining feature extraction methods, and optimizing model training to enhance classification performance.

This section focuses on the dataset used in our study. The dataset utilized in this study comprises retinal images resized and cropped to a maximum size of 1024 pixels. These images, totaling 94,296, have been sourced from two competitions: the 2015 Diabetic Retinopathy Detection and APTOS 2019 Blindness Detection. Annotations indicating the severity of diabetic retinopathy, graded from 0 to 4, accompany each image and subject ID. Notably, for the 2015 images, left or right eye indications are also provided. The dataset encompasses a diverse range of images representing different stages of diabetic retinopathy. The substantial number of images underscores the dataset's utility for training and validation purposes in deep learning algorithms. Additionally, the dataset includes images with real-world imperfections such as artifacts, focus issues, and exposure variations, enhancing its authenticity and reflecting the challenges encountered in clinical practice. Despite these complexities, the dataset remains a valuable resource for developing and evaluating deep learning algorithms for the early detection and management of diabetic retinopathy.

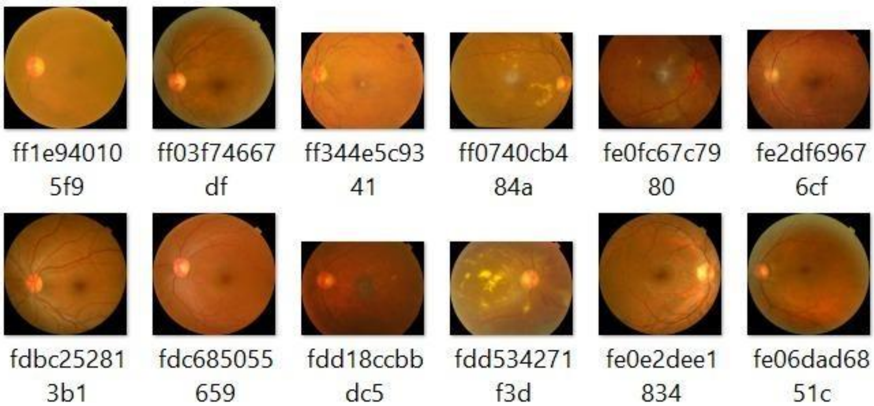

Fig 1. Sample input images

The lack of uniformity necessitated preprocessing to enhance their suitability for subsequent analysis. Through the application of preprocessing techniques illustrated in Figure 2, efforts were made to standardize and optimize the images. This process aimed to refine image quality, ensuring clarity and consistency for accurate analysis and classification within the neural network model.

In preprocessing diabetic retinopathy images, Gaussian blur filtering is utilized to enhance image quality and reduce noise. This technique convolves the image with a Gaussian kernel, effectively blurring the image while preserving subtle details. By reducing high-frequency components, the filter helps standardize images and optimize them for analysis. Gaussian blur preprocessing aids in suppressing noise and artifacts, facilitating more accurate detection and classification of diabetic retinopathy.

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

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

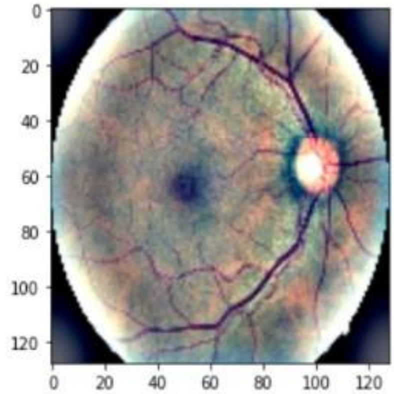

Fig 2. Blur Gaussian Filtering

In this section, we provide a detailed description of the proposed method. Our approach involves implementing and experimenting with three different deep learning (DL) models: CNN, VGG, and ResNet.

The Convolutional Neural Network (CNN) is a dominant architecture in image recognition and classification, prized for its capacity to acquire hierarchical feature representations from raw pixel data autonomously. Its effectiveness stems from hierarchical feature learning, where convolutional layers extract intricate patterns such as edges and textures, pooling layers condense spatial dimensions, and fully connected layers execute classification. Parameter sharing and sparse connectivity enhance computational efficiency, while backpropagation refines network parameters via iterative adjustment. This inherent ability to discern discriminative features from raw pixel data empowers CNNs to attain cutting-edge performance across diverse image recognition endeavors.

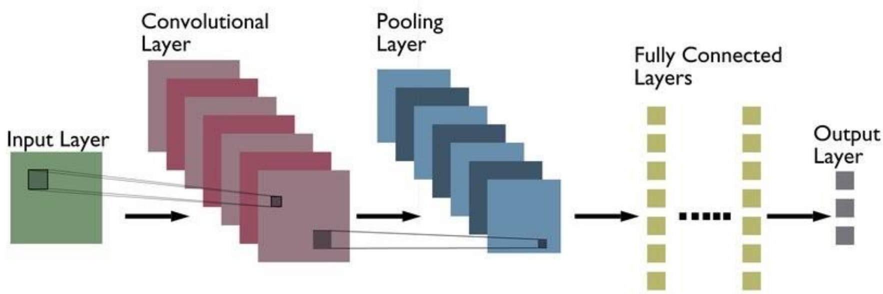

Fig 3. CNN Architecture

VGG16, a prominent convolutional neural network (CNN) architecture developed, is celebrated for its exceptional feature extraction capabilities, enhancing its efficacy across various image processing tasks. Characterized by its deep layers comprising small filter sizes and max-pooling operations, VGG architectures excel in image classification by adeptly learning complex features from raw pixel data. Despite its straightforward design, VGG16 showcases remarkable performance, particularly in object recognition and classification, solidifying its status as a preferred choicein computer vision.

ResNet architecture demonstrated promising outcomes across diverse image classification tasks, making it an ideal choice for our specific aim of detecting and classifying diabetic retinopathy (DR). Its resilience to the vanishing gradient problem ensures robust learning of discriminative features, leading to unparalleled accuracy in identifying minute retinal details. Its ability to handle complex image data effectively has proven invaluable in enhancing the accuracy and efficiency of DR detection systems, aligning well with our DR diagnosis and classification objectives.

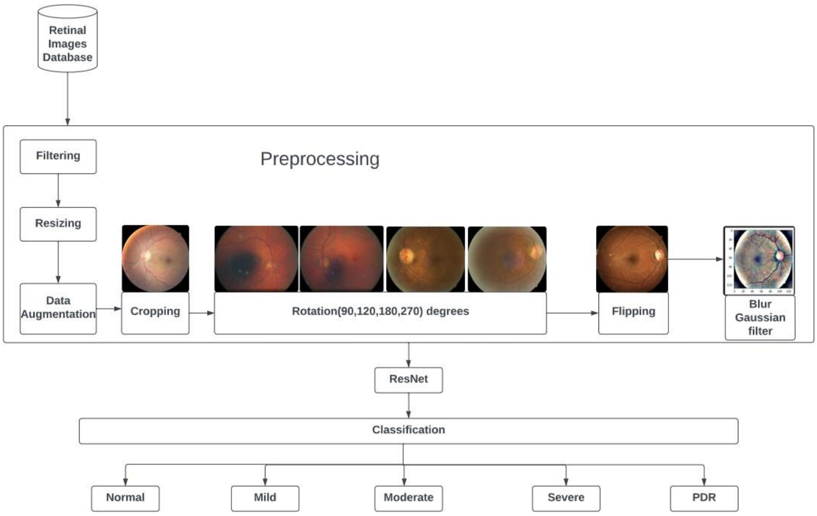

Fig 4. System Architecture

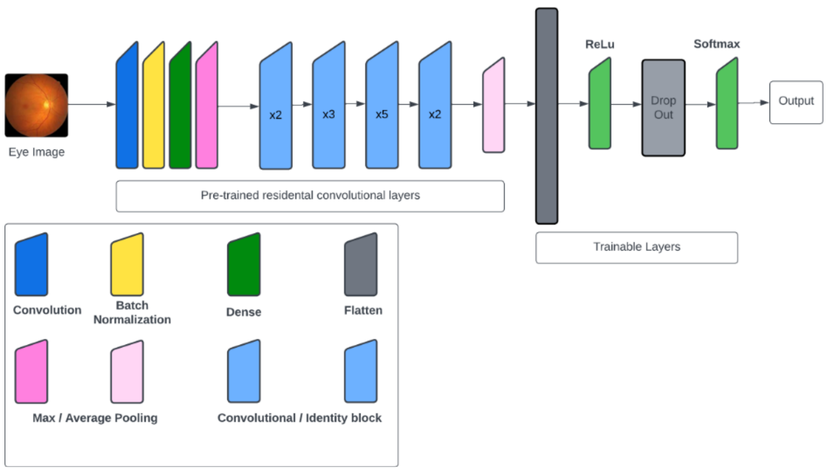

Fig 5. ResNet Architecture

Convolutional Layers: These layers extract features from retinal images, detecting patterns like microaneurysms, hemorrhages, and exudates indicative of DR.

Batch Normalization: Applied after convolutional layers, batch normalization normalizes the activations, aiding in faster convergence and better generalization.

Pretrained Convolutional Layers: Pretrained convolutional layers, often from models trained on large image datasets, provide a starting point for feature extraction, leveraging knowledge learned from diverse images.

Residual Blocks: Residual blocks capture intricate features, mitigating the vanishing gradient problem and enabling the training of deep networks crucial for capturing minute retinal details.

Global Average Pooling Layer: This layer aggregates spatial information from feature maps, condensing them into a single vector, aiding in reducing computational complexity and overfitting.

Flatten Layer: Following the global average pooling layer, the flattening layer reshapes the output into a one-dimensional vector, preparing it for input into fully connected layers.

Dropout: The dropout layer with a dropout rate of 0.5 randomly deactivates a fraction of neurons during training, preventing overfitting and improving generalization by encouraging thenetwork to learn robust features.

Dense Layer: Fully connected dense layers further extract and combine features learned from previous layers, facilitating complex decision-making processes in the network with 2048 units and ReLU activation functions.

Softmax Layer: The softmax layer normalizes the output scores into probability distributions across output classes, aiding in multi-class classification tasks like categorizing different stages of diabetic retinopathy.

Output Layer: The output layer provides the final predictions, indicating the likelihood of each class, i.e., different stages of diabetic retinopathy, based on the learned features extracted from retinal images.

4. RESULTS AND DISCUSSION

The performance of various deep learning models on diabetic retinopathy severity classification using retinal images is examined in Table 1. CNN, VGGNet, and ResNet are the models under consideration. After blur Gaussian filtering, the images were used to train the model, and text accuracy was used to determine benchmarks. Accuracy was tested independently on the training and test sets for each model-filter combination over numerous trials.

Table 2. displays the hyperparameters that were used for training the model. Adam is practical due to its adaptive learning rates, momentum for faster convergence, and efficient memory usage. ReLU activation functions can improve feature learning in convolutional neural networks by encouraging non-linearity, which helps the model capture complex patterns essential for differentiating between phases of diabetic retinopathy and improve the severity classification of the condition.

Table 1. Comparison of Results

Model	TrainingAccuracy	Testing Accuracy
CNN	76	69.4
VGG	75.4	68.5
ResNet	98.31	84.1

Table 2. Parameters used by the models

Epochs	Activation Function	Optimizer	Batch Size
50	Adam	ReLu	32

Across trials, ResNet outperforms various other models on the Gaussian-filtered data, obtaining over 84% test accuracy. ResNet's superior performance when trained with Gaussian images can be attributed to its deep architecture with residual connections. These connections mitigate the vanishing gradient problem, allowing ResNet to capture intricate features crucial for tasks like diabetic retinopathy severity detection. The direct flow of information through skip connections preserves important details, enhancing ResNet's ability to discern subtle image variations. This depth enables ResNet to learn highly discriminative representations, leading to high test accuracy and effective disease severity detection compared to other models.

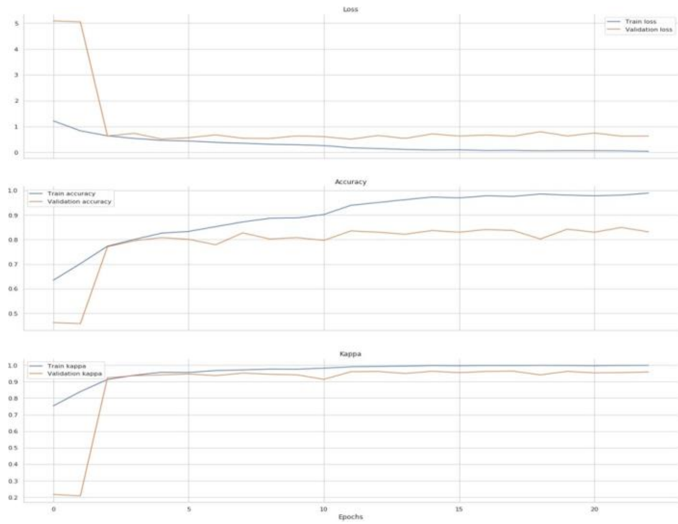

Fig 6. Loss, Accuracy, and Kappa of ResNet

5. CONCLUSION

The application of deep learning in diabetic retinopathy detection within the medical domain has exhibited significant promise and transformative potential. The reviewed studies collectively underscore the efficacy of deep learning models in accurately identifying and classifying retinopathy stages. This is because features have been improved by Gaussian filtering in conjunction with the ResNet model, which has shown a more remarkable 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. Incorporating deep learning technologies streamlines the detection process and potentially revolutionizes the approach to diabetic retinopathy screening on a broader scale. The findings suggest that the synergy between deep learning and medical imaging facilitates early intervention, improving patient outcomes and reducing healthcare burdens.

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