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Diabetic Retinopathy Detection using Deep Learning

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Abstract: - Diabetic Retinopathy threatens vision in diabetics, necessitating swift and accurate detection. This study employs Convolutional Neural Network (CNN), ResNet50, and InceptionV3 for automatic DR identification, achieving a notable 96.18% accuracy over 80 epochs. To enhance robustness, a pre-processing pipeline incorporates Gaussian filtering, CLAHE, median filtering, and top-hat filtering, significantly advancing DR detection accuracy. Evaluation on the APTOS 2019 dataset (1299 training, 279 testing images) reveals great accuracy as well as sensitivity, and specificity, forming a basis for early intervention and vision impairment prevention. This research at the nexus of DL which is also known as deep learning and medical image analyze offers a promising solution for early DR detection. The 96.18% accuracy demonstrates practical viability, positioning our approach as a valuable tool for healthcare practitioners and ophthalmologists in effectively diagnosing and managing diabetic retinopathy.

General Terms: Diabetic Retinopathy, Deep Learning

Keywords: Pattern classification, Detection system, Vision loss prevention, Transfer learning models

I. INTRODUCTION

In the world of rapidly advancing technology, the integration of deep learning algorithms has been recognized as a promising approach to address this pressing healthcare challenge. The significance of diabetic retinopathy being addressed lies in its potential to prevent vision loss, enhance the quality of life for patients, and also mitigate the substantial socioeconomic burden imposed on healthcare systems. The urgency of developing efficient and accessible diagnostic tools is underscored by the profound impact of DR on individuals and its escalating global prevalence.

The utilization of neural networks and comprehensive pre-processing methods was leveraged to achieve timely and precise diagnoses [1]. The focus of our study was the analysis of the APTOS 2019 dataset to assess the system's performance in practical scenarios. Our goal was to add to the expanding

corpus of research on the diagnosis of diabetic retinopathy and provide a practical solution with the potential for a significant public health impact by merging cutting-edge algorithms [2] with rigorous data preparation.

The objective of this paper;

- To introduce a reliable and precise DR detection method based on deep learning technologies.
- To detect diabetic retinopathy in an early stage, to allow it for prompt treatment and control of the problem.
- To identify positive cases of diabetic retinopathy with great sensitivity.

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In the subsequent sections, pertinent studies on diabetic retinopathy are examined. Accordingly, the 3rd section describes the research methodology. Next, Section 4 illustrates the challenges encountered during the research. The final Section 5 represents the conclusion as well as outlines future directions.

II. RELATED WORK

Till date many variant of deep learning models used for pattern classification [28] [29]. In a study conducted by Ramzi Adriman [4], the research explored several deep- learning techniques, including ResNet, DetNet, and DenseNet, to detect and categorize diabetic retinopathy. To extract textural information from the images, local binary patterns (LBP) were employed. Throughout the experiments, the images underwent resizing to different dimensions. The dataset used for these experiments was the “APTOS 2019” dataset. The research results revealed that ResNet achieved an accuracy rate of 96.35%, DetNet achieved 93.99%, VGG16 reached 76.21%, and DenseNet obtained an accuracy rate of 84.05%.

The article titled "A Comprehensive Review of Deep Learning Approaches in Diabetic Retinopathy Analysis" written by Muhammad Waqas Nadeem [7] Paper thoroughly investigates deep learning methods, their uses, frameworks and approaches, in the field of retinopathy analysis. This research covers a range of models such as Deep Convolutional Neural Networks (DCNN) Deep Neural Networks (DNN) Generative Adversarial Networks (GAN) and the U Net architecture all of which were employed in the study. Furthermore, the researchers applied end-to-end trained CNN models for image analysis. By employing this range of diverse approaches, the study accomplished an impressive accuracy rate of 91.6%.

In the study titled "Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks" by Yashasvini R [8], several custom pre-trained models were utilized. These models encompassed the AdaBoost algorithm, which combined InceptionV3, Resnet151, and Inception-ResNet-V2, along with CNN with LSTM, and E-DenseNet. The utilization of these algorithms resulted in the attainment of an accuracy rate of 93.18%. Furthermore, the study also incorporated CNN with DenseNet, leading to a hybrid model that yielded an even higher accuracy of 96.22%. The authors suggest that future work can be carried out by implementing more efficient optimization techniques.

2.1 Dataset

In our research, we employed the Aptos 2019 dataset, which consists of fundus images. The dataset's size is approximately 10GB, and it is primarily divided into five subcategories, focusing on diabetic and non-diabetic retinopathy [10]. has unnecessary noise with low-quality images.

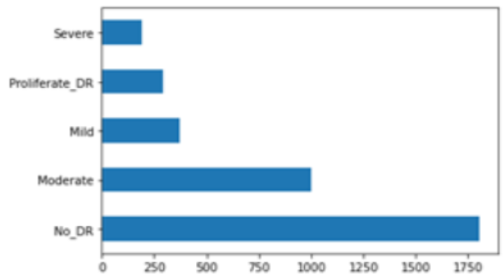

Figure 1 Graph of each class of DR

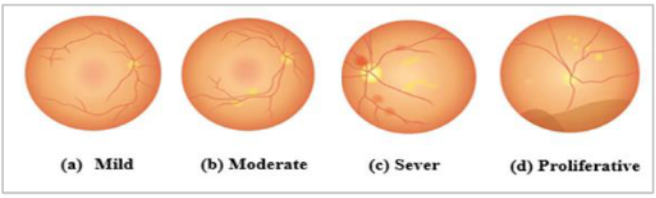

Figure 2 DR Detection Images

Consequently, we decided to eliminate blacked-out images to prevent any undesirable biases in our model's training [11]. This process encompassed both data segregation and data cleaning. The breakdown of these images is given in Figure. 1 and respective images in Figure 2.

III. PROPOSED ARCHITECTURE

Till now a number of several have tried to apply Machine Learning (ML) and the Deep Learning (DL) methods to improve accuracy. However, as per previous research, the optimal highest accuracy for Diabetic detection of available papers was 94%. Our paper is mainly based on the transfer learning models in the scenario of diabetic detection. The deep learning methodology employed in diabetic retinopathy (DR) detection is advanced through the integration of multiple pre-processing techniques and the utilization of various pre-trained models. By incorporating diverse pre-processing techniques such as image normalization, augmentation, and denoising, the quality and standardization of input data are improved, enhancing the model's ability to extract relevant features during training. Accordingly, we have tried to increase the accuracy using Transfer Learning models including CNN, ResNet, VGG16 and InceptionV3 and have achieved 96.18% accuracy. These pre-trained models, having learned representations from extensive datasets, contribute to the model's depth of knowledge, allowing for effective fine-tuning and improved performance in DR detection.

As the dataset is very large and has multiple types of noise in images including salt and pepper noise and low-high brightness of the model so to improve the accuracy of the model instead of giving direct input to the models we did a series of pre-processing techniques. These techniques included Gaussian filtering, CLAHE (Contrast Limited Adaptive Histogram Equalization), median filtering and top-hat filtering [12]. These pre-processing procedures were essential to making the data more suitable for further analysis and modeling. Figure. 3 demonstrate system Architecture.

3.1 Gaussian Filter Algorithm

A Gaussian filter, which is commonly utilized in the field of processing an image and signal processing, serves as a linear filter that applies a smoothing technique by employing a Gaussian function to the input data. Mathematical outline of the Gaussian filter is outlined as follows; For a one-dimensional Gaussian filter:

$$g(x) = \sqrt{\frac{a}{\pi}}\, e^{-ax^2} \qquad (1)$$

Where: (g(x)) is the value of the Gaussian filter at position (x).

(Sigma) is the standard deviation of the Gaussian distribution, which controls the width of the filter's response. A larger (sigma) results in a wider and smoother filter.

For a two-dimensional Gaussian filter:

$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/(2\sigma^2)} \qquad (2)$$

Where: (g (x, y)) is the value of the Gaussian filter at ((x, y)). (Sigma) is the standard deviation, here we used Gaussian filters for tasks such as noise reduction and blurring in image processing because they have a mathematical property known as shift-invariance, which means that they preserve image features while reducing noise.

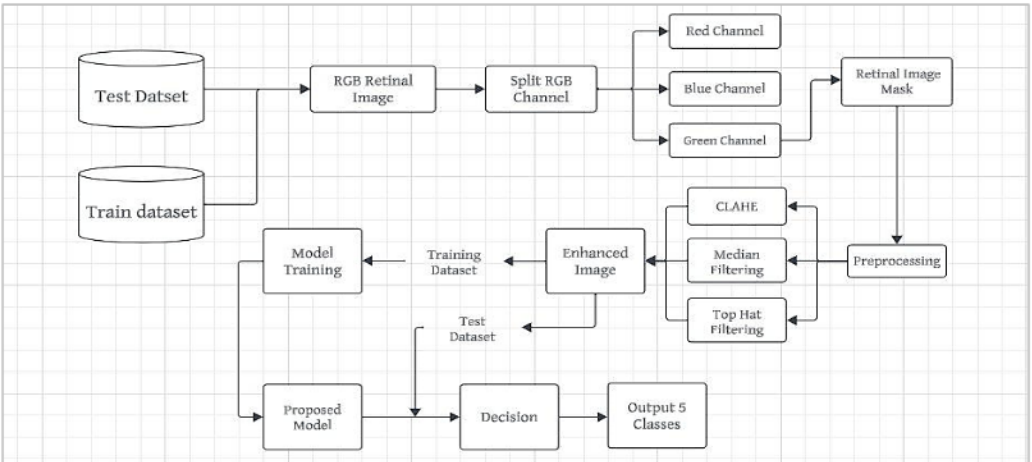

Figure 3 System Architecture

Our experiments demonstrate the significant impact of Gaussian filtering on image quality [13]. By applying this technique as a pre-processing step, we achieved images with reduced noise, but the clarity of the image was not up to the level so we used feature extraction on the image to give a high quality image as input so that our model became more accurate.

3.2 Pre-processing Techniques

For high-quality images, we used pre-processing methods as follows shown in Figure. 4 In our preprocessing pipeline, we introduce an RGB to green channel conversion step to enhance image quality and facilitate feature extraction. The RGB values are converted to grayscale using the NTSC (National Television Standards Committee) formula. The Figure 5 demonstrates the result after applying RGB to the green channel.

A. Image resizing: The green channel image is then resized to 560x720 Standard aspect ratio. It ensures that all images have the same size, making it easier to work with them and train our models. Smaller images use less computer memory and are processed faster, which is important for both training and using the models. However, we need to be cautious not to resize too much, as this can lead to a loss of important details that might affect our model's accuracy. The choice of 560x720 pixels strikes a balance between size and preserving critical information.

B. Median Filtering: In the Median Filtering, we defined a square or rectangular window of a certain size around each pixel in the image. The size of this window is typically referred to as the "filter size" or "window size.". The median of pixels then selected for the result output image Figure 6 demonstrates the median filtering demonstration. Our experiments demonstrated the significant impact of median filtering on noise reduction and image quality enhancement [14]. The inclusion of median filtering in the pre-processing pipeline contributes to more accurate diabetic retinopathy detection and diagnosis.

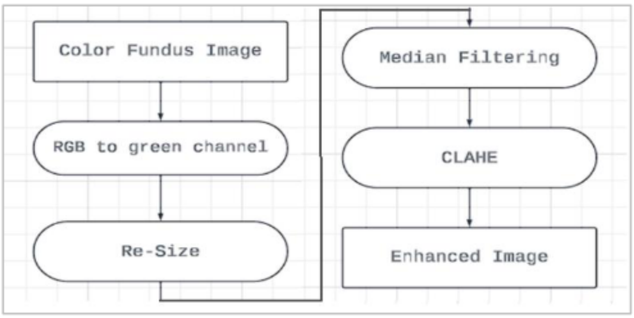

Figure 4 Proposed Pre-processing

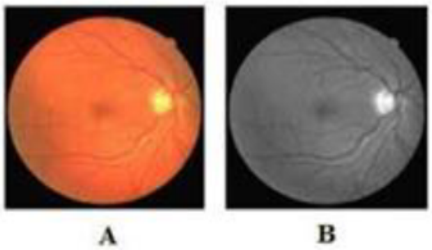

Figure 5 (a) RGB image (b) grayscale image

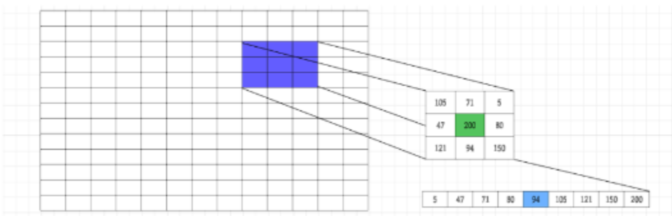

Figure 6 Median Filtering basic architecture

C. CLAHE: To address the issue of noise amplification, the CLAHE technique incorporates a clipping limit. Before calculating the Cumulative Distribution Function (CDF), it employs a predefined threshold to restrict amplification

[15]. Specifically, CLAHE divides the original input image into non-overlapping contextual regions referred to as sub-images, tiles, or blocks. This step effectively addresses contrast and illumination-related challenges. The corresponding output after applying CLAHE is in the given Figure 8.

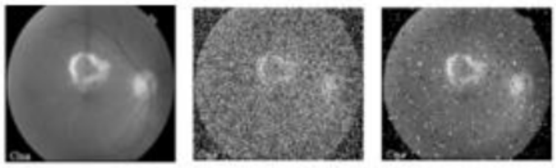

Figure 7 (a) Input (b) noise (c) output

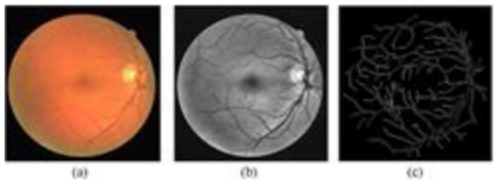

Figure 8 (a) Input (b)After CLAHE (c) Output

To enable unhindered subsequent processing and distinguish the fundus from its background, a binary representation is employed. Specifically, "ones" are employed to signify pixels belonging to the fundus, while "zeros" designate background pixels within a fundus mask. This differentiation becomes more apparent by converting the original RGB fundus image into the HSI color space [17]. In the HSI color system, a distinct channel is dedicated to representing the image's intensity values, aiding in the precise separation of the fundus from its surroundings. To enhance the quality of the created fundus mask, a median filter is applied to eliminate any undesirable noise. The resulting and final mask is visually depicted in Figure 9. The incorporation of top-hat filtering as a boundary enhancement technique in our image processing pipeline is a valuable approach to improve the accuracy of boundary detection in diabetic retinopathy images [18]. This step effectively addresses the challenges associated with boundary detection and contributes to the advancement of diagnostic methods in this critical field. After applying Top hat filtering we got the final result as given in Figure 10. After Preprocessing the image, we applied multiple CNN models including ResNet-50, CNN, Inceptionv3, VGG-16 and CNN. The highest accuracy was given by Inception V3

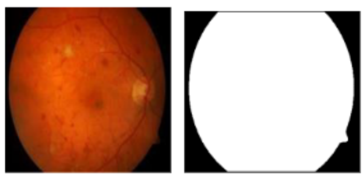

Figure 9 (a) Input image (b) mask

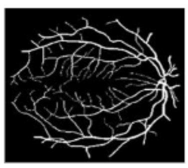

Figure 10 Top hat filtered image

3.3 Model Architecture

A. CNN: A Convolutional Neural Network (CNN) [30] processes input data, often images, through convolutional layers that use filters to extract features such as edges or textures. Activation functions introduce non-linearity after convolutional operations. Pooling layers reduce spatial dimensions of feature maps, aiding computational efficiency. Fully connected layers follow, connecting neurons across layers. Dropout, a regularization technique, is applied to fully connected layers to prevent overfitting by randomly deactivating neurons during training. Flattening converts the output of the last convolutional or pooling layer into a one-dimensional vector, preparing it for fully connected layers. The final output layer, task-dependent, produces results, employing softmax for image classification or varying structures for different tasks like object detection. This sequential process, from input processing to final output, characterizes the architecture and functionality of CNNs.

$$\textbf{Sigmoid Function: } f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

$$\textbf{Tanh Function: } f(x) = \frac{(e^{x}-e^{-x})}{(e^{x}+e^{-x})} \quad (4)$$

$$\textbf{Relu Function: } Max\ (x, 0) \quad (5)$$

B. ResNet 50: In the ResNet-50 architecture, the initial layer processes input images of 224x224 pixels with three color channels. The network begins with convolutional layers employing convolution, batch normalization, and ReLU activation functions to identify features. A key feature is the use of residual blocks with skip connections, simplifying gradient flow during training. ResNet-50 comprises 50 layers organized in stacked residual blocks, each focusing on learning residuals, streamlining the training of deep networks. Global average pooling follows, reducing spatial dimensions for a fixed-size feature vector. The architecture concludes with a fully connected layer using softmax activation, mapping features to output classes, facilitating tasks like image classification. The model's output is a probability distribution for potential classes, utilized in tasks such as predicting the category of input images.

C. VGG 16 Model: VGG16 is a convolutional neural network architecture utilized for image recognition. What sets it apart is its streamlined structure consisting of just 16 weight- bearing layers, avoiding the need for an excessive number of hyper parameters. It is widely regarded as one of the top choices for vision-related tasks.

D. InceptionV3 Model: In the Inception V3 model, an efficient approach to reduce the grid size involves expanding the activation dimensions of the network's filters. As illustrated in Figure 11, let's consider a scenario where we have an n*n grid with k filters. After the reduction process, this leads to a grid size of n/2 × n/2 with 2k filters. This transformation is achieved through the combination of two parallel blocks of convolution and pooling, which are subsequently concatenated.

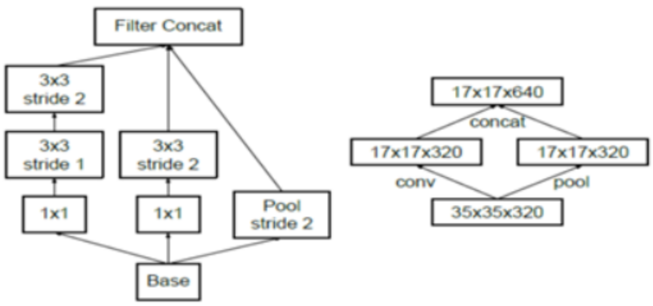

Figure 11 Expanded filter banks of Inception V3

However, in the end inception v3 gives the highest accuracy because Inception-V3 is a relatively deep and complex network with many layers and a variety of convolutional modules, including the inception modules. This complexity allows it to learn a wide range of features at different scales and complexities, which is beneficial for detecting fine details and patterns in medical images like retinal scans. These modules use parallel convolutional filters with different kernel sizes to capture features at multiple scales. This enables the network to detect both small and large structures in the retina, which is important for diabetic retinopathy diagnosis.

IV. RESULT

The paper extensively discusses the practical applicability of the proposed technique for medical professionals and its potential impact on the diagnosis of diabetic retinopathy. It emphasizes the importance of timely detection for prompt treatment and control and highlights the innovative approach utilizing deep learning algorithms to facilitate accurate diabetic retinopathy diagnosis. The integration of advanced image processing techniques aims to provide a reliable and precise detection method, and the model's performance evaluation demonstrates its efficacy. We employed the APTOS 2019 dataset, comprising 1,299 samples for the DR training set and 279 samples for the DR testing set. The model we developed uses Batch size of 50 and epochs 80 are consider. The work demonstrates significantly improved accuracy when trained with the APTOS 2019 dataset. Specifically, our model achieved a remarkable maximum accuracy of 99.88% during training, surpassing our initial expectations. Furthermore, it achieved an outstanding accuracy rate of 96.18%, which stands as the highest among all current accuracy metrics. As depicted in Figure 12 below, a clear trend emerges in the model's loss. The loss value exhibits a gradual decline as the number of epochs increases. It is worth noting that the training experiments encompassed various CNN models, and among them, the Inception V3 model demonstrated the highest accuracy. The test data must be prepared for this dataset, which is meant to be used for model training and prediction. Table 2 presents a comparison of the accuracy achieved by several pre-trained models on the testing dataset. Furthermore, VGG16 is suitable for intricate patterns in APTOS 2019 due to its constant architecture. InceptionV3 is outstanding with its multi-scale features and inception modules. As a result, the computational intensity was additionally evaluated. Besides, in Table 3 the proposed model was compared to a number of deep learning concepts like transfer learning, AlexNET and many more algorithm. With the InceptionV3 model, the suggested model obtains the optimal accuracy of 96.18%. The proposed model shows the highest level of accuracy when comparing the different models in the above Table 2.

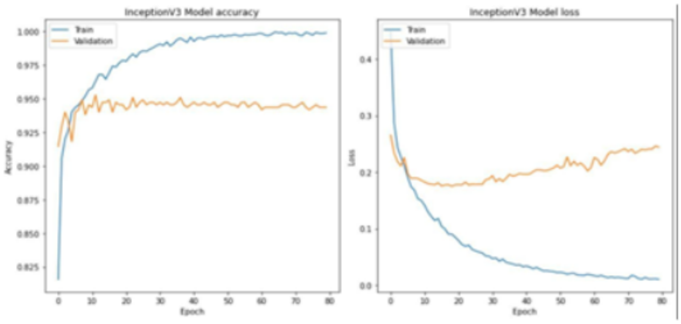

Figure 12 Graph of Loss and Accuracy of the model

Table 2 Accuracy of each model in retinopathy classification

Method	F1	Accuracy	Sensitivity	Specificity
CNN	0.9212	0.9399	0.9461	0.919
VGG16	0.9521	0.9472	0.9502	0.969
Resnet50	0.9061	0.9163	0.8920	0.962
INC. V3	0.9780	0.9618	0.9678	0.972

Table 3 Results Obtained by Various Models

Ref	Technology	Accuracy
[21]	TL on pre-trained Inception-Res-Net-v2	72.33% And 82.18%
[22]	Alex Net Deep transfer learning algorithms	Alex net model 95.2%
[23]	Two CNN models	78%
[25]	CNN Models	88.72%
[26]	Optimized Wavelet based model, SVM Model	94.83%
[27]	K nearest neighbor, ML Algorithm	95 %
Proposed Model	Inception V3 model, CNN ,VGG16	96.18%

V. CONCLUSION

Our meticulous study on diabetic retinopathy classification, utilizing the APTOS 2019 dataset, thoroughly compares pre-trained models, ranging from generic CNN to advanced architectures like InceptionV3, VGG16, and ResNet50. The findings reveal InceptionV3's superiority, justified by its inception modules and multi-scale features, positioning our model at the forefront with an exceptional accuracy of 96.18%. However, considering real-world usability, several important considerations and limitations must be acknowledged. The system's performance across diverse demographic groups and external datasets requires thorough investigation to ensure generalizability. Enhancing interpretability through explainable AI methods is crucial for transparency in medical decision-making. Additionally, scrutinizing the model's susceptibility to misclassifications, especially with varying image qualities or artifacts, is imperative. Continuous refinement, validation, and adaptation to real-world challenges are essential for ensuring the system's robustness. Looking ahead, future research should focus on addressing these considerations, exploring alternative architectures, and refining the model for broader clinical applicability. Despite these challenges, our study lays a foundation for AI to become a cornerstone in preventive and personalized medicine for diabetic retinopathy detection and beyond.

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