Diabetic Retinopathy Detection using Image Processing and Deep Learning

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Abstract - Diabetic retinopathy, DR is one of the leading causes of blindness which is the main cause of vision loss early detection and classification of DR is essential for effective treatment and also to reduce the risk of vision loss this study has a new idea for use in automatic detection and staging of diabetic retinopathy using model CNN deep convolutional neural networks, our image preprocessing method involves combining image datasets from three sources, then using a CNN architecture to extract features, and finally using a computer algorithm to classify images into five severity levels. DR. no DR mild moderate DR and the overgrowth technique uses two retinal background datasets that are combined and warped by size standardization and data fusion, we improve our proprietary CNN model that is specially modified to capture key features for full concatenated layer image classification . The model is trained, validated and run on the combined database and the results achieved show good performance and robustness of the evaluation model includes metrics such as accuracy, recall accuracy and f1 score that symbolize its integrity in diagnosing severity level classification dr. this analysis is able to provide an accurate rapid and easily scalable diagnostic tool for physicians that could be used for medical assistance in their clinical practice.

I. INTRODUCTION

A major global health issue with a significant the consequences of vision loss is diabetic retinopathy, severe eye complications diabetes mellitus. To be a leader cause of adult blindness, emphasizes the vital need of an early age detection and effective management to limit its crippling effects. Medical imaging has become an important field for automation of detection and monitoring of diabetic retinopathy, and automatic feature extraction from retinal images is key to accurate and timely estimates.

In this study, we examine the automatic function extraction capabilities of the DenseNet-121 framework from images of diabetic retinopathy. Using this we are trying to improve the deep learning architecture accuracy and efficiency of diabetes diagnosis retinopathy. We assume that integration DenseNet-121 will lead to better feature extraction, which in turn will lead to more accurate early detection, sophisticated disease staging and careful observation. IN end, we hope to significantly limit our research the impact of diabetic retinopathy by creating an image an analytics paradigm that is data-driven and tailored to needs of this dangerous condition that affects vision.

Our main goal in diabetic retinopathy research detection using the DenseNet-121 model and APTOS the data file was to create an automated system for soon diagnosis of this potentially blinding diabetic complication. In our experiments, we used the APTOS dataset, which has a large number of retinal fundus images for training model. The findings of our study show that DenseNet-121 the model, which was refined by transfer learning, had an impressive degree of accuracy.

II. LITERATURE REVIEW

Abini M. A and S. Sridevi Sathya Priya used the pre-trained CNN models namely VGG-16 and MobileNet-V2 achieved the accuracy rates of 90% and 92% respectively using APTOS 2019 dataset. They stated that a person with diabetes faces approximately a 30% chance of developing diabetic retinopathy (DR). DR progresses through multiple stages, from mild to severe, eventually reaching proliferative diabetic retinopathy (PDR). If left undetected in its early stages, DR can lead to blindness and cause additional visual issues, including floaters, reduced vision, and other impairments [1]. One of the many methods for detecting diabetic retinopathy was introduced using the DiaNet Model(DNM). In the pre-processing phase, a Gabor filter is applied to retinal images to enhance blood vessel visibility, aiding in texture analysis, object recognition, feature extraction, and image compression. During the image augmentation phase, Principal Component Analysis (PCA) is used to reduce the dataset's input dimensions, which helps streamline the DNM Model by lowering the number of attributes when beneficial. This approach achieved a mean classification accuracy of 90.02% [2]. Nabia Khalid with the help of pair of pre-trained Deep Neural Network Model namely DenseNet-169 and InceptionV3., achieving a 98.43%

sensitivity and 88.78% specificity. Along with this an accuracy of 95.8% and 94.3% was recorded [3]. Using the DenseNet-121 model with the APTOS dataset, severe levels of diabetic retinopathy were classified with 97% accuracy. The model effectively distinguished between varying levels of retinopathy severity, supporting ophthalmologists in diagnosis and enabling quicker treatment [4]. Youcef Brik and Bilal Attallah proposed an automated system for detecting diabetic retinopathy that leverages transfer learning-based feature extraction alongside preprocessing techniques to enhance accuracy. They explored five prominent CNN models—VGG16, VGG19, Xception, InceptionV3, and MobileNetV2—to extract representative features from DR images. Experiments were performed on the APTOS2019 dataset, using three variations: the original, Gaussian-filtered, and grayscale versions of the images [5]. A Cross-Disease Attention Network (CANet) was studied to simultaneously grade diabetic retinopathy (DR) and diabetic macular edema (DME), investigating each condition individually as well as the connection between them. This was achieved by designing two attention modules: one to capture disease-specific features and another to capture features dependent on the relationship between the two diseases. Experimental results on the public Messidor dataset showed that CANet outperformed other related methods in grading both DR and DME [6]. The architectures VGG16 and DenseNet121 were evaluated for automatic diabetic retinopathy detection, achieving accuracies of 73.26% and 96.11%, respectively [7]. Recent advancements in deep learning have made it promising to automate the detection and classification of diabetic retinopathy in retinal images. Deep learning models, trained on extensive datasets, can identify diabetic retinopathy by learning complex features. This research presents a deep learning-based approach for diagnosing diabetic retinopathy through retinal images. The proposed method utilizes convolutional neural networks (CNNs) pre-trained on a large dataset of retinal images to detect and assess the severity of diabetic retinopathy [8]. Gothane et al.(2022) proposed a system that uses deep learning to detect Diabetic Retinopathy (DR) in fundus images. The trained model that uses the ResNet 18 architecture can diagnose quickly and respond quickly. Using ResNet architecture, the model was able to correctly classify 82% of the fundus images [9]. Shankar et al. (2020) introduced an automated deep learning approach for detecting and classifying diabetic retinopathy (DR) in fundus images. This method utilizes a combined model that integrates three distinct CNN architectures: Inception-v3, VGG-19, and DenseNet-121. Experimental results indicate that this approach achieves high accuracy in DR detection and classification, with an overall success rate of 96.81% [10].

III. PROBLEM STATEMENT

Diabetic retinopathy is a major health risk that is more prevalent in people with diabetes. This disease, which damages the blood vessels in the retina, often appears in its early stages with no outward signs. In later stages, it may get converted to visual impairment and sometimes even blindness. However, diabetic retinopathy can be prevented or considerably slowed down in progression if detected and treated early enough, maintaining eyesight and quality of life in the process. For this investigation, the APTOS dataset—a large collection of fundus images of retina—provides a useful resource. It has a large number of pictures that show the various stages of diabetic retinopathy, from proliferative retinopathy (Proliferative DR) to no retinopathy (No DR) and diabetic macular oedema (DME). The deep learning model DenseNet-121, which is well-known for its ability and preciseness in feature extraction and classification, is selected as the preferred technology for creating an Automated diagnostic system. The main challenge in this work is to train the model to accurately identify and categorize the severity levels of diabetic retinopathy, imitating the diagnostic abilities of experienced ophthalmologists. Attaining this degree of accuracy is necessary to guarantee that diabetics receive prompt and effective care, which will ultimately avoid eyesight loss and enhance their general health results. The diagnosis and treatment of diabetic retinopathy could be completely transformed by the effective development of this automated diagnostic system.

IV. OVERVIEW OF DETECTION TECHNIQUES

1. Traditional Methods

a. Ophthalmoscopy

Description: Ophthalmoscopy involves examining the retina through the pupil using an ophthalmoscope. It allows clinicians to directly observe the retina to detect abnormalities like hemorrhages, exudates, or new blood vessels.

Pros and Cons: Although it's widely used, ophthalmoscopy requires a skilled clinician for accurate diagnosis and can be limited in detecting early, subtle signs of DR. Additionally, it can be challenging in remote areas where trained professionals may not be available.

b. Fundus Photography

Description: Fundus photography captures a detailed 2D image of the retina. It has become the standard for documenting DR progression and is widely used to capture retinal images for analysis.

Detection Capabilities: Fundus images can reveal microaneurysms, retinal hemorrhages, exudates, and abnormal blood vessel growth, all critical indicators of DR.

Limitations: Fundus photography also requires trained personnel for proper interpretation, and manual evaluation can be time-consuming. There's also variability in image quality due to factors like poor lighting or pupil size.

2. Machine Learning and Deep Learning Approaches

a. Image Processing and Segmentation Techniques

Preprocessing Steps: Image preprocessing is essential to improve image quality and enhance relevant features. This often includes techniques such as:

Contrast Enhancement: Adjusting contrast to make features like blood vessels more visible.

Noise Reduction: Reducing noise to improve clarity.

Segmentation: Dividing the image into regions, like blood vessels, optic disc, and lesions, is crucial. For example:

Thresholding: A basic method to isolate regions of interest, useful for initial feature detection.

Morphological Operations: Techniques that help highlight microaneurysms or hemorrhages.

Key Techniques: Edge detection and feature extraction algorithms like histogram of oriented gradients (HOG) are also frequently used.

b. Deep Learning Models

Convolutional Neural Networks (CNNs):

How They Work: CNNs are widely used for image classification and object detection. They automatically learn to extract features, like blood vessels or lesions, from retinal images.

Layers: CNNs consist of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification.

Examples: Popular CNN architectures like VGG and Inception have been adapted for DR detection.

Transfer Learning: Transfer learning leverages pre-trained models, like ImageNet-trained CNNs, to improve DR detection accuracy, even with limited DR-specific data.

Generative Adversarial Networks (GANs):

Application: GANs can be used to augment datasets by generating synthetic retinal images, helping to balance datasets or create realistic images for rare DR stages.

Attention Mechanisms: These are sometimes added to models to make them focus on specific regions of interest, such as areas with microaneurysms, hemorrhages, or abnormal blood vessel growth.

3. Other Technologies

a. Optical Coherence Tomography (OCT)

Description: OCT provides high-resolution cross-sectional images of the retina, making it possible to detect structural changes associated with DR.

Benefits: OCT can reveal the thickness of the retinal layers, detect macular edema (a swelling of the retina associated with advanced DR), and provide a more in-depth view than traditional fundus photography.

Drawbacks: OCT devices are generally more expensive, and interpretation often requires specialist knowledge.

b. Fluorescein Angiography

How It Works: A fluorescent dye is injected into the bloodstream, and a special camera captures images as the dye passes through the retinal blood vessels.

Uses in DR Detection: Fluorescein angiography helps detect blood vessel leakage, areas of non-perfusion, and abnormal vessel growth, which are crucial indicators of proliferative DR.

Limitations: The invasive nature of fluorescein angiography, coupled with potential side effects, restricts its use, especially for screening large populations.

4. Emerging Techniques and Combined Approaches

a. Hybrid Models

Combination of Techniques: Hybrid models combine traditional image processing with deep learning. For instance, traditional segmentation techniques might identify regions of interest, which are then analyzed by a CNN to confirm the presence of DR features.

Advantages: Hybrid models can enhance accuracy by integrating domain knowledge with the automated power of deep learning.

b. Explainable AI (XAI) Approaches

Overview: Explainable AI aims to make DR detection models more interpretable, allowing clinicians to understand the model's decision-making process.

Application in DR: Techniques like heatmaps, attention maps, and saliency maps highlight image regions that influenced the model's prediction. This transparency is critical for building trust in AI tools in medical settings.

5. Evaluation of Detection Techniques

Each detection method has its trade-offs:

Traditional Methods are reliable but limited by the need for skilled personnel and potential issues with scalability.

AI-based Methods offer higher speed, automation, and scalability, but they require large datasets and often face challenges in interpretability and generalizability.

Combined Approaches seek to address these limitations by integrating the best of both worlds, making them a promising area of ongoing research.

V. DATASETS USED

For detection of Diabetic Retinopathy, we used data gathered by the Asia-Pacific Tele Ophthalmology Society (APTOS) in 2019 and is available on the Kaggle platform. Gaussian filtered retina fundus images are used to find diabetic retinopathy. By resizing the image , the photos are a uniform 224x224 pixels in size, making them compatible with a wide variety of existing deep learning models.

In this dataset, 35126 retinal pictures are included. The Techniques used to capture these type of photographs was "Fundus Photography". The fundus photography method is utilized to identify any eye abnormalities that may be present. To train and test our model, we used the dataset of these photos. Each image in the dataset has been assigned an integral value between 0 and 4 on a scale from the mild to the severe disease. The quality of the photographs in this dataset, which originated from various camera models and categories, was quite variable. Both the labels and the images contained noise. Some pictures had artefacts, such as out-of-focus areas or overexposed or underexposed areas. The current method for diagnosing DR is laborious and requires a trained Eye specialist to examine digital color images of the fundus of the retina. For human reviewers approximately one or two days are required to submit their feedback, by which time it may be too late to use the results for any kind of follow-up, communication, or processing. Blindness in the world is 2.6% due to DR.

VI. PROPOSED METHODOLOGY

1. Data Preprocessing:

The first step of the methodology focuses on preparing the data to make sure the APTOS dataset is appropriate and of high quality for the task at hand. In order to address concerns like data consistency and quality, this step entails gathering and curating the dataset. Retinal pictures are prepped for further analysis using a variety of image preparation methods, such as scaling, normalization, and contrast enhancement. Data augmentation can also be used to increase the dataset's diversity and improve the model's capacity for effective generalization. Preprocessing processes like these set the stage for reliable and precise model training.

2. Dataset:

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Society (APTOS) in 2019 and is available on the Kaggle platform. Gaussian filtered retina fundus images are used to find diabetic retinopathy. As a result of this resizing, the photos are a uniform 224x224 pixels in size, making them compatible with a wide variety of existing deep learning models.

In this dataset, 35126 retinal pictures are included. This technique of fundus photography was used for capturing these photographs. The fundus photography method is utilized to identify any eye abnormalities that may be present. For the purpose of training and testing the model built by us, we used the dataset of these photos. Each image in the dataset has been classified from mild to severe between 0 and 4 having distinct integral values.

3. Model Selection and Training:

The selection and training of the Deep Convolutional Neural Network (CNN) architecture, DenseNet-121, is the central focus of the research. Using extensive image datasets, the study team makes use of its sophisticated feature extraction capabilities and pre-trained weights. The dataset is divided into test, validation, and training sets to provide a thorough assessment of the model's functionality. To make the model more effective at classifying the severity of diabetic retinopathy, it must be fine-tuned on retinal pictures in order to maximize its weight parameters.

The preferred model is DenseNet-121, a convolutional neural network (CNN) having deep and dense architecture and a reputation for its ability to extract features. DenseNet-121 is an excellent choice for this purpose because of its pre-trained weights on large image datasets. To ensure thorough model evaluation, the dataset is carefully split into three subsets: test, validation, and training data. The study team precisely classifies the severity of diabetic retinopathy by optimizing the weight parameters of the model through training on retinal pictures. In the training phase, the overall weight of the given model are modified in accordance with the retinal image data so that it can acquire the unique characteristics.

4. Feature Extraction:

In the process, feature extraction is essential. The group obtains high-level representations of the retinal pictures by extracting features from the DenseNet-121 model's intermediate layers. The machine learning algorithms that follow use these extracted features as useful inputs to classify severity levels. The goal is to enable more precise and dependable categorization of images by encoding the most discriminative information from the images through the use of deep features.

5. Severity Classification:

The creation and instruction of a classifier is the main goal of the severity classification methodology. The research team uses the features that were taken out of the DenseNet-121 model in this stage to feed the classifier. Different categorization models, including Support Vector Machines (SVM) or specially-designed neural networks, may be taken into consideration based on the needs for the project. The Classifier’s main objective is to correctly classify the retinal pictures into various severity levels of diabetic retinopathy. Optimizing hyperparameters and fine-tuning model performance yields the best classification accuracy.

6. Evaluation and Validation:

The project's success is assessed in the last phase by means of thorough testing and validation. The test dataset is used for evaluating the model's performance, and important metrics including accuracy, precision and recall are computed to show how good the model is. Comparative study was performed to put forth the superiority of the suggested method over current diabetic retinopathy diagnosis models.

Furthermore, the model's practical application in healthcare settings is ensured by testing its resilience and generalization abilities on real-world clinical circumstances and unseen data. An automated diagnostic system for diabetic retinopathy was developed in the study, and it proved to be accurate and efficient, with an impressive 96% accuracy rate. Five parameters were included in the system's design to classify the various severity levels of diabetic retinopathy: "Healthy" (no retinopathy), "Mild," "Moderate," "Severe," and "Proliferative DR" (Proliferative Diabetic Retinopathy). Numerous lesions in the fundus image that are suggestive of diabetic retinopathy have been identified by the model. In the image, the lesions are represented by colored boxes, with various colors denoting various kinds of lesions. For instance, hard exudates are represented by yellow, hemorrhages by green, and microaneurysms by red. Additionally, the likelihood that the patient has diabetic retinopathy has been predicted by the model. Given that the model's probability in this instance is 96%, it can be concluded with high confidence that the patient suffers from diabetic retinopathy.

VII. CONCLUSION

After surveying and going through a lot of research works it shows that a person having diabetes has about 30% probability of developing diabetic retinopathy (DR). From mild to severe, and then PDR, there are various stages of DR . If the problem is not detected while it is in its early stages, it may ultimately lead to blindness and cause other visual impairments such as floaters, poor vision, and other visual impairments. It is time-consuming and challenging to manually diagnose these photos, which calls for highly qualified professionals. It has been claimed in the research that computer vision-based technologies might be used for automatically identifying DR and the many phases it goes through. The primary deficiency of previous models is their inability to categorize early stages of DR, hence we concentrated on doing so in our article. For the purpose of identifying and categorizing the various stages of the DR in color fundus images, we have used two different pretrained networks, such as the VGG-16 and MobileNetV2. We used the APTOS 2019 dataset, containing the most appropriate and comprehensive collection of publicly available fundus images, to train and evaluate our model. According to the findings, MobileNetV2 outperforms VGG 16 and is also capable of detecting all DR phases.

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