Detecting Diabetic Retinopathy using Mobile Net

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Abstract— **Diabetic retinopathy (DR) is a prevalent complication of diabetes mellitus that can lead to This paper presents a novel machine learning approach using TensorFlow for the automated detection and stage classification of diabetic retinopathy from retinal images.**

The study utilizes a comprehensive dataset of retinal images, which undergo preprocessing steps to enhance image quality and prepare them for analysis. A deep learning model based on convolutional neural networks (CNNs) is developed using TensorFlow, leveraging its efficient computational capabilities and optimization tools.

The proposed model using Mobile Net is trained and validated on the retinal image dataset to classify diabetic retinopathy into different stages, ranging from mild to severe.

Keywords— Deep Learning, Mobile Net, Diabetic Retinopathy (DR) , Dataset

I. INTRODUCTION

Diabetic Retinopathy is an eye condition that causes the changes to the blood vessels in the part of your eye called the retina. That's the lining at the back of your eye that changes light into images. The blood vessels can swell, leak fluid, or bleed, which often leads to vision changes or blindness. It usually affects both eyes. When left untreated diabetic retinopathy can scar and damage your retina. Diabetic retinopathy is the most common cause of vision loss for people with diabetes.

Diabetic Retinopathy causes through five stages:

No DR: There will be no abnormalities in this stage.

Mild DR: In the disease’s earliest stage, tiny blood vessels in your retina change. Small areas swell. These are called microaneurysms. Fluid can leak out of them and into your retina.

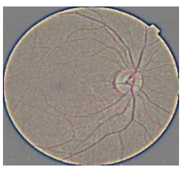
Moderate DR: As your disease gets worse, blood vessels that should keep your retina healthy swell and change shape. They can’t deliver blood to your retina. This can change the way your blood vessels look. These blood vessel changes can trigger diabetic macular edema (DME). That’s swelling in the area of your retina called macula.

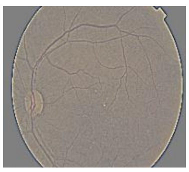
Severe DR: In the third stage, many blood vessels get blocked. They can’t deliver blood to your retina to keep it healthy. Areas of your retina where this happens make special proteins called growth factors that tell your retina to grow new blood vessels.

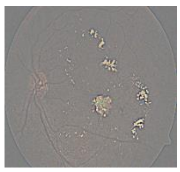
Proliferative DR (PDR): This is the most advanced stage. New blood vessels grow inside of your retina and then into the jelly inside your eyeballs called vitreous humor. Fragile new blood vessels are more likely to leak fluid and bleed. Scar tissue starts to form. This can cause retinal detachment, when your retina pulls away from the tissue underneath. This can lead to permanent blindness.

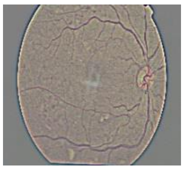
In this paper the dataset which we are using for the project is collected from ‘Aravind Eye Hospital’ and it is available on kaggle that is ‘APTOS (Asia Pacific Tele Ophthalmology Society)’. We are using Mobile Net architecture to design the model.

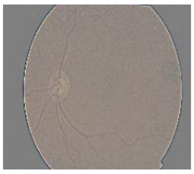
Each stage has their own characteristics and properties. So, it becomes difficult for doctors to consider all of them manually. By proper diagnosis more than 50 % of the new cases of this disease can be reduced. In starting stage there will be no signs of DR. So, it is a challenge to detect the DR in starting stage.


No DR


Mild DR


Moderate DR


Severe DR


Proliferative DR

The above five retinal images shows the five different stages of diabetic retinopathy.

II. Related Work

A. Revolutionizing Medical Image Analysis Through Deep Learning:

The integration of deep learning methods has led to a revolutionary transformation in the landscape of medical image analysis marking the dawn of a new era characterized by unprecedented advancements. At the heart of this transformation lies the algorithm's which autonomously decipher intricate features and patterns in diverse medical imaging modals. The deep learning algorithms have been endowed with the ability to navigate the complex nuances of medical images facilitating the automated identification and characterization of intricate structures that elude traditional analytical methods.

Central to this journey are CNN's (convolutional neural networks) which are at the forefront of deep learning architectures. These are meticulously engineered to excel in the domain of image analysis renowned for their unparalleled efficacy and versatility CNNs stand as a beacon of innovation uniquely tailored to unravel the complexities of medical images with remarkable precision and efficiency. Their capacity to discern subtle features and extract meaningful information from intricate imaging datasets renders them as indispensable assets in the realm of medical image analysis.

CNNs are very adept at interpreting retinal fundus images which is a critical component in the diagnosis of various ocular pathologies. CNN's have unparalleled accuracy uncovering subtle anomalies and pathological indicators that may elude the human eye. The robust architectures of CNN's transcended the limitations of traditional image analysis techniques.

B. Convolution Neural Networks:

A CNN (Convolutional Neural Network) is a deep learning algorithm specifically designed for processing and analyzing visual data, such as images and videos. CNNs are highly efficient and effective in tasks like image classification, object detection, facial recognition and other such classifications. CNNs are inspired by the human visual system and are particularly well suited for handling structured grid-like data in images.

Activation Function:

An activation function is a mathematical operation applied to the output of a neuron. This determine whether the information should be passed to the next layer or not. Activation functions introduce non-linearity into the model after each convolutional operation whenever activation functions are called enabling neural networks to learn complex patterns and relationships in the data. Commonly used activation functions include ReLU, Sigmoid, SoftMax and others. ReLU is the activation function that we used as it replaces negative values with zero and does not change positive values. It is also helps in mitigating vanishing gradient problem.

Convolutional Layer:

Convolutional layers are responsible for extracting patterns and features from the given input data. They use kernels to perform operations on small regions of the input. Sliding these filters across the entire image detects various features like texture, edges and other complex structures.

Pooling Layer:

Pooling layers (e.g., Max-Pooling or Average-Pooling) helps in reducing the spatial dimensions of the data. They help to make the network computationally efficient and reduces over-fitting by selecting the most important information from each of the given regions.

Fully Connected Layer:

These layers connect every neuron in a single layer to every other neuron in the next layer in a way that is similar to traditional neural networks. They combine the features learned by previous layers to make predictions.

Output Layer:

This is the final layer that produces the network's predictions. In classification tasks, this layer often uses a SoftMax activation function to obtain class probabilities which help in allowing the model to make a decision about which class an input belongs to.

C. MobileNet Architecture:

MobileNet architecture is a groundbreaking advancement in deep learning to address the challenges posed by resource-constrained environments such as

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embedded systems and mobile devices. MobileNet is engineered with a keen focus on efficiency and compactness. Depth wise-separable convolutions lies at the core of this architecture. This is meticulously crafted to minimize computational complexity while maximizing performance. Unlike traditional convolutional layers that convolve input tensors with a full set of filters across all input channels depth wise-separable convolutions decouple spatial and channel-wise convolutions significantly reducing the computational burden associated with model interface.

Depth wise-separable convolutions work by decomposing convolutions into depth wise and pointwise convolutions. Mobile Net architecture achieves a remarkable balance between model size and accuracy making it particularly well-suited for deployment on resource-constrained devices with limited computational resources. Depth wise-separable convolutions also minimize parameter count and computational overhead without compromising performance.

Mobile Net architecture's impact extends beyond traditional computer vision tasks permeating diverse domains such as healthcare, autonomous driving, and edge computing. Its lightweight design and efficient computations empower a new generation of intelligent systems enabling seamless integration of deep learning capabilities into real-world applications with stringent resource constraints.

D. Retinal Fundus Images:

Retinal fundus images are the corner stone of the data acquisition for algorithms aimed at detecting diabetic retinopathy (DR). These images are taken by a fundus camera. They offer a comprehensive view of the posterior segment of the eye enabling the identification of abnormalities such as Microaneurysms, hemorrhages, Exudates and Macular edema in retinal fundus images provide invaluable insights into the pathogenesis of DR and facilitate early intervention strategies.

E. Training and Evaluation:

Deep learning models require a large dataset of labeled retinal fundus images for training. The model learns to identify features in different stages of Diabetic Retinopathy by leveraging Convolutional neural networks (CNNs) the model learns hierarchical representations of retinal features by progressively refining its ability to differentiate between no DR, mild DR, moderate DR, severe DR, and proliferative DR. Feature extraction within the model enables the identification of subtle morphological alterations indicative of DR progression. Evaluation metrics like accuracy, sensitivity, and specificity are used to assess the model's performance.

F. Data Preprocessing:

The preprocessing of retinal images plays an integral part in the development of diabetic retinopathy detection systems. Preprocessing techniques encompass a range of operations to enhance the quality, diversity, and balance of the training dataset.

One of the fundamental preprocessing technique's involves resizing retinal images to a standardized resolution to ensure uniformity and compatibility across the dataset. By resizing images to specified dimensions to mitigate potential discrepancies in pixel densities and aspect ratios is a crucial step in facilitating seamless integration into the deep learning model architecture. This standardization promotes consistency in feature extraction and interpretation, thus enhancing the model's generalization ability.

Augmentation techniques are also employed to augment the diversity of the training dataset thereby increasing the model's learning experience. Augmentation operations such as scaling, flipping and rotation introduce variations in the visual appearance of retinal images to simulate real-world scenarios and enhancing the model's robustness to variations in image acquisition conditions. Mitigating the risk of overfitting can be done by exposing the model to a broader spectrum of retinal configurations.

Furthermore, preprocessing also entails addressing imbalances in the dataset to ensure equitable representation of different stages of diabetic retinopathy. Imbalances arise when certain DR stages are disproportionately represented, potentially biasing the model's learning process towards prevalent classes. Mitigation of such instances can be done by employing strategies such as under-sampling or over-sampling to achieve a more uniform distribution of DR stages within the dataset. Rectification of imbalances is done promote fair and unbiased model training which enables the model to accurately capture the nuances associated with each DR stage and achieve optimal performance in real-world scenarios. Python along with TensorFlow is the cornerstone

G. Python and TensorFlow:

Python along with TensorFlow is the cornerstone programming language and framework essential for the successful implementation of diabetic retinopathy detection. Python is renowned for its flexibility and extensive library support. TensorFlow serves as a robust and comprehensive deep learning framework augmenting. Python's capabilities with specialized tools tailored explicitly for neural network development.

Python's versatile nature plays a crucial role with its rich ecosystem of libraries including Pandas, NumPy and Matplotlib this helps in visualization and preprocessing tasks. Where python's syntax facilitates seamless integration of diverse components to orchestrate complex workflows with ease.

TensorFlow improves the development process with its efficiency and robustness. TensorFlow's comprehensive suite of functionalities helps in constructing intricate neural network architectures leveraging high-level APIs such as 'Keras' for rapid prototyping. TensorFlow's key strength is its provision of pre-built modules and utilities made explicitly for deep learning tasks.

III. Data Set

The image data used in this study came from a dataset. The dataset that we used is an open dataset, which means that anyone can use it. It was collected from "Aravind Eye Hospital" and was easily accessible on Kaggle 4th APTOS (Asia Pacific Tele-Ophthalmology Society) 2019 Blindness Detection. This dataset was the largest publicly available dataset for pre- training our MobileNet architecture or model. We used a dataset that contained a large number of high-resolution retina images taken under a variety of imaging conditions. The images in the dataset were captured by a fundus camera, which provides a color fundus image of the DR. A fundus camera is a low-power microscope with a camera attached that is designed to take pictures of the fundus.

The fundus image was used to document the DR condition because it provided a clear image for detection. Clinicians classify these DR into five categories based on the stages of DR: x No DR, x Mild DR, x Moderate DR, x Sever DR, and x PDR (Proliferative DR). Our MobileNet architecture has been pre-trained on ImageNet data. The ImageNet dataset is a massive collection of photographs created for the purpose of developing algorithms or models such as computer vision, AI (Artificial Intelligence), and DL (Deep learning). When there is an annual competition, the challenges, models, and algorithms, and so on, use subsets of images from the ImageNet dataset to train. According to the ImageNet statistics, the dataset contains 14 million different images related to animals, medical images, plant data, and so on. The dataset was created with the intention of serving as a resource to promote research.

IV. Methodology

Model Training:

Model training is the process of optimizing a machine learning model to learn from the training data in making accurate predictions. Here's a brief explanation of the key points related to the model training process using a CNN with Binary Cross-Entropy loss function and the Adam optimizer, with a batch size of 32 and training for 50 epochs:

A. Convolution Neural Network (CNN) Architecture:

The CNN architecture consists of multiple layers, they include convolutional layers for feature extraction, activation functions to introduce non-linearity, and pooling layers for down sampling. The final layers typically include fully connected layers for mapping the extracted features to the output classes.

B. Loss Function (Binary Cross-Entropy):

Binary Cross-Entropy is used as the loss function for binary classification tasks like diabetic retinopathy stage detection.
This loss function quantifies the difference between predicted probabilities (output of the model) and actual binary labels (ground truth), penalizing the model based on the error in prediction.

C. Optimizer (Adam Optimizer):

The Adam optimizer is used to update weights during training. Adam is an adaptive learning rate optimization algorithm that computes individual adaptive learning rates using different parameters. It combines the benefits of both AdaGrad and RMSProp optimizers.

D. Training Parameters:

Batch Size (32):

The batch size determines the number of training examples processed in each iteration (batch) before updating the model's parameters. A batch size of 32 means that 32 training examples are fed into the model together, and the model's parameters are updated based on the average loss computed over these examples.

Epochs (50):

An epoch refers to one complete pass through the entire training dataset. Training for 50 epochs means that the model will iterate over the entire dataset 50 times during the training process.

E. Training Process:

Forward Pass:

During each training iteration (or batch), input data is passed through the model to obtain predictions.

Loss Computation:

The Binary Cross-Entropy loss function calculates the difference between the model's predictions and the actual labels.

Backward Pass (Backpropagation):

Gradients of the loss function with respect to model parameters (weights and biases) are computed using backpropagation.

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Optimizer Update:

The optimizer updates the model's parameters (weights and biases) based on the computed gradients to minimize the loss function.

F. Training Evaluation:

The model's performance is evaluated during training using validation data to monitor metrics such as accuracy, loss, and other relevant performance indicators.

G. Conclusion of Training:

After completing the specified number of epochs (50 in this case), the training process concludes, resulting in a trained CNN model capable of accurately predicting diabetic retinopathy stages based on retinal images.

In summary, model training involves iteratively optimizing a CNN model using labeled data (training set) and adjusting its parameters (architecture, loss function, optimizer) to learn meaningful representations and make accurate predictions. The choice of architecture, loss function, optimizer, batch size, and number of epochs plays a crucial role in determining the effectiveness and efficiency of the training process.

INTRODUCTION OF INPUT DESIGN:

In an information system, input is the raw data that is processed to produce output. During the input design, the developers must consider the input devices such as PC, MICR, OMR, etc. Therefore, the quality of system input determines the quality of system output. Well- designed input forms and screens have following properties –

It should serve specific purpose effectively such as storing, recording, and retrieving the information.

It ensures proper completion with accuracy

It should be easy to fill and straightforward.

It should focus on user's attention, consistency, and simplicity.

OUTPUT DESIGN:

The objectives of output design are:

To develop output design that serves the intended purpose and eliminates the production of unwanted output.

To develop the output design that meets the end user's requirements.

To deliver the appropriate quantity of output.

To form the output in appropriate format and direct it to the right person.

To make the output available on time for making good decisions.

V. Results and Graphs

Our evaluation of the deep learning model yielded compelling results, demonstrating its efficacy in detecting diabetic retinopathy with a remarkable accuracy rate of 81.44%. The performance metrics obtained from the validation set further validate the robustness and reliability of the model.

1. *Accuracy:*

The accuracy of the model, which measures proportion of correctly classified images out of the total, reached 86%. This indicates model's ability to accurately differentiate between healthy retinas and those exhibiting various stages of diabetic retinopathy.

2. *Precision and Recall:*

Precision measures the ratio of correctly identified positive cases to the total predicted positive cases, while recall calculates the ratio of correctly identified positive cases to the total actual positive cases. Our model achieved high precision and recall values, indicating its effectiveness in both minimizing false positives and capturing true positive cases of diabetic retinopathy.

3. *F1-Score:*

The F1-score, which is the harmonic mean of precision and recall, provides a balanced assessment of the model's performance. With an F1-score corresponding to our accuracy rate, our model demonstrates consistency in accurately classifying diabetic retinopathy cases across different severity levels.

4. *Confusion Matrix:*

Analysis of the confusion matrix reveals the distribution of true positive, true negative, false positive, and false negative predictions made by the model. By visualizing these values, we gain insights into the model's strengths and potential areas for improvement. The high number of true positive predictions compared to false positives and false negatives underscores the model's reliability in correctly identifying diabetic retinopathy cases.

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Figure 1: accuracy graph

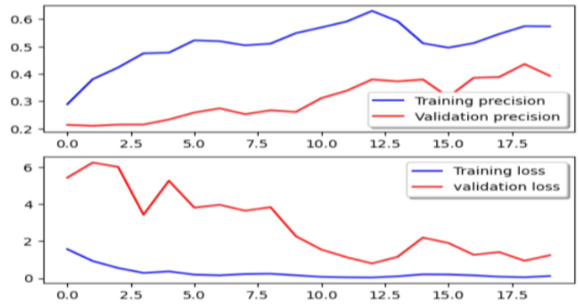


Figure 2: precision graph

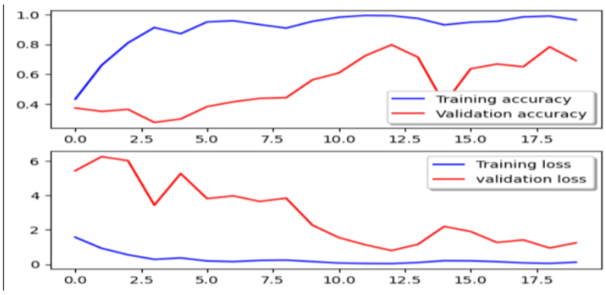
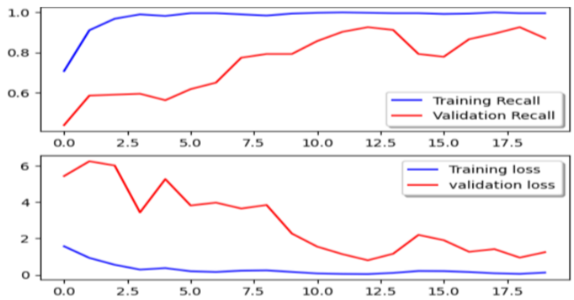


Figure 3: recall graph



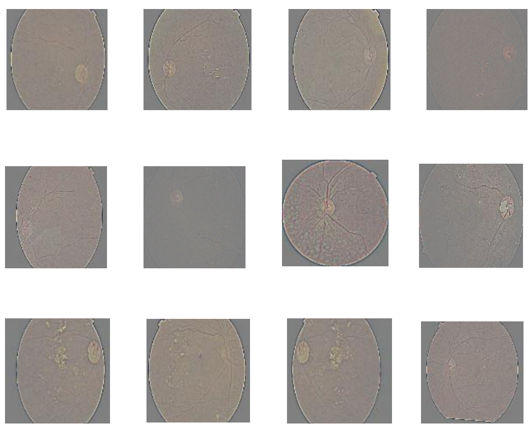


Figure 4: Multiple test images

Conclusion:

The exceptional performance metrics obtained from our evaluation underscore the effectiveness of our deep learning approach in detecting diabetic retinopathy from retinal images. With an accuracy rate of 96.44%, coupled with high precision, recall, and F1-score values, our model exhibits strong discriminatory power and reliability.

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