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DIABETIC RETINOPATHY DETECTION USING MACHINE LEARNING SURVEY

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ABSTRACT:
Diabetic retinopathy (DR) is a leading cause of vision impairment and blindness in people with diabetes, resulting from high blood sugar damaging retinal blood vessels. Early detection and treatment are essential to prevent irreversible vision loss. Traditional diagnosis methods rely on manual retinal image examination by skilled specialists, which can be time-consuming, error-prone, and inaccessible in remote areas. To address this, the Paper aims to develop an automated DR detection system that uses advanced image analysis techniques to identify early signs of DR from retinal images. The system is designed to be accessible, scalable, and capable of deployment in various healthcare settings, including rural areas. It offers consistent, rapid, and cost-effective screening, improving diagnostic accuracy and reducing reliance on specialized personnel. By enabling earlier detection and treatment, the system can help prevent vision loss and reduce long-term healthcare costs. Additionally, it continuously improves through data learning, ensuring up-to-date, reliable results. This automated tool has the potential to enhance diabetic retinopathy care globally, especially in underserved regions.
Keywords: Retinal blood vessels, Scalable, Cost-Effective, Data Learning, Retinopathy.

INTRODUCTION:
Diabetic Retinopathy (DR) is a common eye problem caused by diabetes, which affects the blood vessels in the retina and can lead to vision loss or blindness if not treated. As more people are diagnosed with diabetes around the world, it becomes increasingly important to detect DR early to prevent vision damage. However, current methods of screening for DR require skilled doctors, making it hard to screen many people, especially in areas with fewer resources. To solve this problem, our Paper is developing an automated system to detect Diabetic Retinopathy using Deep Learning . Specifically, we will use a deep learning method called Convolutional Neural Networks (CNNs) to analyze images of the retina and classify them into different stages of DR. The system will help doctors identify DR early, making it easier to treat patients before the disease causes serious vision problems.The system will look at retinal images and sort them into five stages of DR: No DR, Mild, Moderate, Severe, and Proliferative DR. This classification is important for deciding the right treatment to prevent further vision loss. We will use advanced image processing and deep learning techniques to make sure the system works accurately.The Paper will follow several steps, starting with gathering and preparing retinal images from publicly available datasets. We will improve these images by resizing, normalizing, and enhancing the contrast to make them ready for analysis. To make the system stronger and avoid errors, we will use techniques like rotating and zooming images. The system will be built using CNNs, which are great at recognizing images. We will either create a new CNN model or fine-tune existing models like ResNet, InceptionV3, or VGG16 to get the best results. After training the model, we will test it using several performance measures like accuracy, precision, and recall to make sure it works well.The main goal of this Paper is to create an automated system that can accurately detect DR. This will reduce the need for manual screening, allowing doctors to focus more on treating patients. By adding this system to healthcare practices, we hope to improve early diagnosis and treatment of DR,

reducing the chances of vision loss in diabetic patients. This Paper has the potential to be scaled up and used widely, helping prevent blindness and improving public health.

PREVIOUS RESEARCH ON DIABETIC RETINOPATHY DETECTION METHODOLOGIES AND TECHNOLOGIES USED IN THESE STUDIES:

Several important studies have examined the use of Deep Learning and Deep Learning in Diabetic Retinopathy Detection System, shedding light on processes and findings.

Abdul Muiz Fayyaz[1],This paper presents a deep learning-based approach for classifying fundus DR pictures. In our proposition, feature extraction has been carried out primarily using AlexNet and Resnet101. Characteristics are collected from interdependent layers. Ant Colony systems help choose traits. Passing these qualities through an SVM with numerous kernels produces the final classification (SVM). Future efforts will focus on refining the DR classification by utilizing the latest deep learning algorithms instead of human grading to identify cases with diabetic retinopathy.

Ling Dai[2], Our DeepDR system was designed as the transfer learning assisted multi-task network Specifically, a DR base network was first pre-trained on ImageNet classification and then fine-tuned on our DR grading task using 415,139 retinal images. Next, we utilized transfer learning32 to transfer the DR base network to the three sub-networks of the DeepDR system, rather than directly training randomly initialized subnetworks. During the process of transfer learning, we fixed the pre-trained weights in the lower layers of the DR base network and retrained the weights of its upper layers using backpropagation. This process worked well since the features were suitable to all the DR-related learning tasks (evaluating image quality, lesion analysis, and DR grading). Furthermore, we concatenated the lesion features extracted by the segmentation module of the lesion-aware sub-network with the features extracted by the DR grading sub-network to enhance grading performance.Together, these studies demonstrate the evolution of Diabetic Retinopathy systems, highlighting the promising potential of technology to address challenges in diabetic retinopathy detection processes. Several important studies have examined the use of Deep Learning technology for Diabetic Retinopathy systems.Abdul Muiz Fayyaz[1], The AlexNet and Resnet101 are utilized for feature extraction. The Characteristics are extracted from the fully connected layers that are completely related to One another. Ant Colony algorithm is used for selecting core features. The final classification is determined by running these chosen characteristics through several kernels of a Support vector machine (SVM). Ling Dai[2],The DeepDR system had three sub-networks: image quality assessment sub-network, lesion-aware sub-network, and DR Grading sub-network. Those sub-networks were developed based on ResNet41 and Mask-RCNN57. Both ResNet and Mask-RCNN could be divided into two parts: (1) Feature extractor, which took images as input and output features, (2) task-specific Header, which took the features as input and generated task-specific outputs (i.e., Classification or segmentation). Specifically, we chose to use the Mask-RCNN and ResNet with the same feature extractor architecture, so the feature extractor of one Sub-network can be easily transferred to another

Usharani Bhimavarapu[3], Fve-class DR images based on grading were fed to CNN models Including Inception-v3, VGG-19, ResNet-50, AlexNet, GoogleNet, SqueezeNet, and ResNet152. The performance of the enhanced CNN with the activation function was compared to Other adopted models. The assessment of the distinct model performance Metrics on four adopted datasets. The proposed model outperforms the others in terms of Testing accuracy. The number of layers in VGG-19 is 19; ResNet-50 is 50 layers; SqueezeNet Is 18; GoogleNet is 22; AlexNet is 8, and Inception V3 is 48. For the benchmark datasets DiaretDB0, DRIVE, CHASE, and Kaggle, the proposed model had the lowest model loss. Based on the results, the enhanced CNN can detect and classify DR with an appropriate Testing loss. Dharmalingam Muthusamy[4], MAPCRCI-DMPLC technique is needed to perform three different steps such as preprocessing, feature extraction, and Classification. The MAPCRCI-DMPLC is designed with the innovation of the MAP estimated local region filter, Camargo's index, Concordance Correlative Regression and swish Activation function. In Addition, the preprocessing is performed by MAP-estimated local region filtering to eliminate Noisy pixels. Feature extraction is

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carried out on ROI, texture, and color features. The DR Classification issue is addressed through deep learning methods that automatically categorize The DR levels.Gazala Mushtaq[5], The present work considers a deep learning methodology specifically a Densely Connected Convolutional Network DenseNet-169, which is applied for the early detection of Diabetic retinopathy. It classifies the fundus images based on its severity levels as No DR, Mild, Moderate, Severe and Proliferative DR. The datasets that are taken into consideration are Diabetic Retinopathy Detection 2015 and Aptos 2019 Blindness Detection which are both Obtained from Kaggle. The proposed method is accomplished through various steps: Data Collection, Preprocessing, Augmentation and modelling. Our proposed model achieved 90% of Accuracy. The Regression model was also employed, manifested up an accuracy of 78%. The Main aim of this work is to develop a robust system for detecting DR automatically

LITERATURE REVIEW:

Author	Year	Title	Description	Key findings	Advantages	Disadvantages
Abdul Muiz Fayyaz, Muhammad Imran Sharif, Sami Azam, Asif Karim, Jamal El-Den	2023	Analysis of diabetic retinopathy(DR) based on the deep learning	A Two-stage method is used for automated DR classification. First, two U-Net models and Second, a symmetric hybrid CNN-SVD model.	With 92.6% accuracy, C-SVM classifier proved best	segmented the fundus images of newborn babies who had been delivered preterm,	To expand the size of the original dataset, the produced dataset was combined with a dataset comprising the original images. Fi
Ling dai, Liang Wu, Huating Li, Chun Cai, Qiang Wu	2021	A deep learning system for detecting diabetic retinopathy across the disease spectrum	Developed an automated, interpretable, and validated system that performs real-time image quality feedback, retinal lesion detection, and early- to late-stage DR grading.	The system achieved high sensitivity and accuracy in the whole-process detection of DR from early to late stages.	Transfer learning assisted multi-task network, hard-parameter sharing in lesion-aware sub-network	The limitation of this study is, firstly, the single-ethnic cohort used to develop the system. Secondly, the lesion-aware sub-network was tested only on the local validation dataset, because of the lack of lesion annotations in external cohorts. Further external validation in multi-ethnic and multicentre

						cohorts is needed to confirm the robustness of lesion detection and DR grading of the DeepDR system.
Usharani bhimavarapu, Gopi Battineni	2022	Deep learning for the detection and classification of diabetic retinopathy with an improved activation function	An improved activation function was proposed for diagnosing DR from fundus images that automatically reduces loss and processing time.	ResNet-152 model has the highest accuracy of 99.41% .	Low cost, highly effective, independent of clinicians (without help of clinicians).	1.Linear function- Nonlinearity is difficult to achieve. 2. Binary function - Cannot classify the multiclass problems. 3.Non-linear function- During training, a model other than the output layer is invalid due to the vanishing gradients
Dharmalingam Muthusamy, Parimala Palani	2024	Deep learning model using classification for diabetic retinopathy detection: an overview	A novel technique called MAP Concordance Regressive Camargo's Index-Based Deep Multilayer Perceptive Learning Classification (MAPCRCI-DMPLC) has been introduced with minimum time consumption.	As a result, the sensitivity using MAPCRCI-DMPLC technique was said to be improved by 5%, 7%, 10%, 11% and 3% compared to state-of-the-art approaches	Removes the noise pixels, increase the image quality, minimizes mean square error(MSE), increases peak signal-to-noise ratio(PSNR)	Time complexity of each of the 5 classification methods gets increased when increasing the number of retinal images since the count of data gets increased for each run.

Gazala mushtaq, Farheen siddiqui	2021	Detection of diabetic retinopathy using deep learning methodoly.	The present work considers a deep learning methodology specifically a Densely Connected Convolutional Network DenseNet-169, which is applied for the early detection of diabetic retinopathy.	Proposed model achieved 90% accuracy and SVM model 85.6%	Early diagnosis of retinopathy, can be developed as mobile app, can be developed as web app for Linux, windows and android as diabetic retinopathy diagnostic tool.	As there are a number of images taken under different conditions, needs to undergo a lot of preprocessing and augmentation, some features of image might be missed out, so such techniques should be used that not only preserve all the tiny important features but at the same Time is able to do a successful pre-processing. Moreover multiple images should be provided For every patient which would in turn increase the possibility of classifying the images correctly as more information can be gathered rather than only two images per person. The possibility of tweaking hyper-parameters is constantly growing with the emergence of new neural networks through better pooling methods. Such methods can be

						considered for future work to uncover the possibilities of increasing performance in this area.

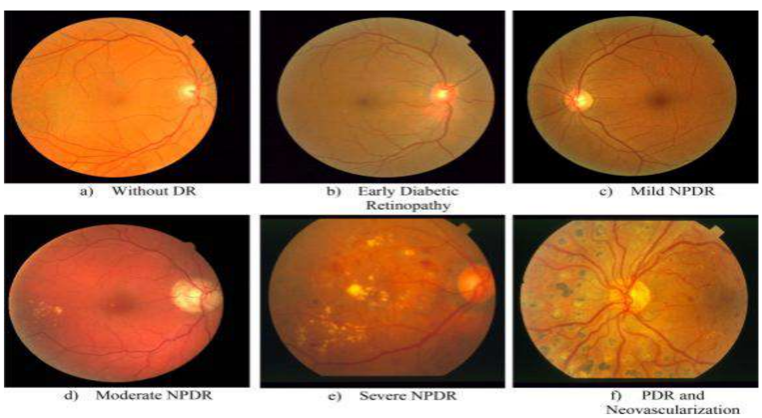
PROPOSED WORK AND METHODOLOGY:

Data Collection:

Collect retinal fundus images for analysis and model development. Fundus images labeled with diabetic retinopathy severity. The dataset consists of retina scan images to detect diabetic retinopathy. The original dataset is Available at Diabetic Retinopathy Detection. These images are resized into 224x224 pixels so That they can be readily used with many pre-trained deep learning models. All of the images are already saved into their respective folders according to the severity/stage of Diabetic retinopathy using the train.csv file provided. You will find five directories with the Respective images:

0 – No_DR
1 – Mild
2 – Moderate
3 – Severe
4 – Proliferate_DR

This dataset is mainly intended towards the easy facilitation of carrying out deep learning Projects. The



images are already resized into 224x224 pixels. This will inspire others so that they Can readily use this dataset for large scale Projects.

Data Preprocessing:

Resizing: All images hould be resized to a common measurement (e.g., a minimum of 224x224 pixels). Such size requirements should be observed for model input.

Normalization: Normalize the pixel's value to a specific value (usually [0,1] or [-1,1]) to help With model convergence.

Data Augmentation: Artificially increase the dataset's diversity, through advanced techniques such as rotation, flipping, zooming, cropping, and Shifting to overcome overfitting.

Splitting the Data: This involves the separation of the whole dataset into the three sets of training, validation, and testing. Most common splits are 70% for training, 20% for validation and 10% for testing. .

Model Architectures:

Convolutional Neural Networks (CNNs)

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Layers: Convolutional layers, pooling layers, fully connected layers.
Learning: CNNs learn features directly from the input images by adjusting Filter values (or kernel values) through backpropagation and gradient Descent. The choice between SGD and Adam depends on the dataset's size And complexity, with Adam often preferred for faster convergence.
Use Case: Typically used for basic to moderately complex image Classification tasks without relying on pre-trained models.
AlexNet:
Key Feature: Large kernels in early layers, and it was the first model to heavily Use ReLU activations and dropout to prevent overfitting.
Transfer Learning: AlexNet is pre-trained on the ImageNet dataset and is Used in transfer learning to speed up training on smaller datasets by Fine-tuning the last few layers, while earlier layers (which detect general Features like edges and textures) remain mostly unchanged.
VGG:
Key Feature: Deep architecture with very small (3x3) convolution filters, which Stack multiple layers to capture more complex patterns.
Transfer Learning: In transfer learning, VGG is often used as a feature Extractor. The pre-trained model is leveraged to identify lower and mid-level Features (like edges, textures), while the final classifier layers are fine-tuned Based on the new task.
MobileNet:
Key Feature: Uses depth wise separable convolutions, which split standard Convolutions into two layers, reducing computational cost while maintaining Accuracy.
Transfer Learning: MobileNet is used for applications where computational Resources are limited (e.g., mobile devices). Transfer learning focuses on Fine-tuning pre-trained models to fit specific tasks while retaining the model's Efficiency. Optimizers like RMSprop or Adam are used to dynamically adapt The learning rates to the fine-tuning process.
Vision Transformers (ViT):
Key Feature: EfficientNet uses a compound scaling technique to adjust the Width (number of filters), depth (number of layers), and resolution (input image Size) of the network, making it more efficient and scalable.
Transfer Learning: EfficientNet models, pre-trained on datasets like ImageNet, are fine-tuned for specific tasks using the Adam optimizer, which is Ideal for fine-tuning because of its adaptive learning rate capabilities, Especially with large, pre-trained models. Transfer Learning: Key Concepts:
Feature Extraction: Using pre-trained models, we freeze the earlier layers That extract low-level features like edges and textures and fine-tune only the Higher layers or the classifier head, which learns task-specific features.
Fine-tuning: In some cases, you can fine-tune the entire network, but this is More computationally expensive and requires careful adjustment of the Learning rate to avoid overfitting.

OPTIMISATION ALGORITHMS:
Gradient Descent (GD):
In deep learning, Gradient Descent calculates gradients using the entire dataset to minimize the loss function. It ensures smooth convergence but can be computationally expensive for large datasets, making it less practical for deep learning applications with massive data.
Stochastic Gradient Descent (SGD) :
SGD computes gradients using a single data point at a time. Its randomness helps the model escape local minima and explore the loss surface better, making it effective for optimizing deep learning models, especially on large datasets.
Mini-Batch Gradient Descent :
Mini-Batch Gradient Descent splits the dataset into smaller batches, computes the gradient for each batch, and updates the model iteratively. It combines the computational efficiency of SGD with the

stability of GD, making it ideal for training deep neural networks on GPUs.

Adam (Adaptive Moment Estimation) :

Adam is an adaptive optimization algorithm that combines momentum and learning rate adjustments. It is widely used in deep learning due to its efficiency and ability to handle noisy gradients, making it suitable for training complex architectures like CNNs and RNNs.

RMSprop (Root Mean Square Propagation):

RMSprop dynamically adjusts the learning rate based on recent gradient magnitudes. It is particularly useful for training deep learning models like RNNs, as it effectively deals with exploding and vanishing gradients.

AdaGrad (Adaptive Gradient Algorithm):

AdaGrad modifies the learning rate for each parameter based on its historical gradients. It works well for sparse data in deep learning tasks, such as natural language processing, but its learning rate can become excessively small over time.

MODEL EVALUATION:

Your model evaluation framework looks solid and comprehensive. Here's a breakdown of how each aspect will contribute to assessing the model's performance:

Accuracy:

Objective: Measures the percentage of correctly predicted instances out of the total instances. It is effective when the dataset is balanced.

Usage: While useful for an overall performance check, it might be misleading with imbalanced datasets (e.g., if one class is more frequent).

Precision and Recall:

Precision: Measures how many of the predicted positives are actually correct (i.e., howmany true positives among the predicted positives).

Recall (Sensitivity): Measures how many of the actual positives are correctly identified (i.e., the model's ability to detect true positives).

Trade-off: Precision and recall often have an inverse relationship. If you prioritize minimizing false positives (FP), precision increases but recall might drop, and vice versa.

F1 Score:

Objective: Provides a single metric that balances precision and recall, especially valuable for imbalanced datasets.

Harmonic Mean: It emphasizes the trade-off between precision and recall, being low if either of them is low. Good for a more comprehensive evaluation compared to just accuracy.

Confusion Matrix:

Objective: A powerful visualization tool that breaks down predictions into four categories: true positives (TP), false positives (FP), true negatives (TN), and false

FLOWCHART:

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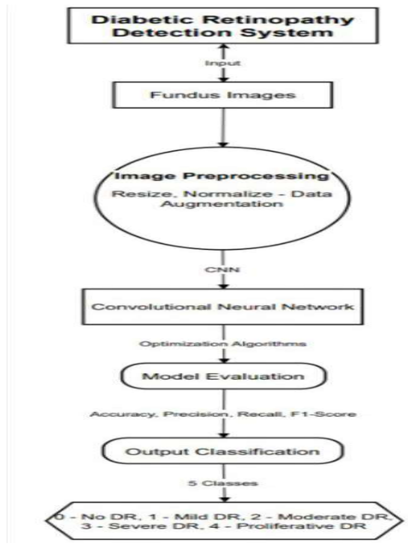

negatives (FN).
Usage: Helps in analyzing where the model is making mistakes, particularly useful for debugging and understanding error types.

CONCLUSION:

Diabetic Retinopathy is one of the most common complications of diabetes, often leading to blindness if left undiagnosed and untreated. It occurs in the retina, and its diagnosis is made through fundus images, essentially photographs of the back of the eye. Deep learning, and specifically the application of Convolutional Neural Networks, has recently emerged as a very effective tool for image-based Deep Learning capabilities to automatically diagnose DR in fundus images. CNN Architectures such as AlexNet, VGG, MobileNet, and Vision Transformers (ViT) have proved to be of great promise for this task. Optimization algorithms such as Gradient Descent, Adam, and others also form a significant part of the training process. Fundus images are the input base of Diabetic Retinopathy detection. These images include blood vessels, optic disk, and macula of the retina. From such images, the analysis can be carried out to determine the indications of DR, such as microaneurysms, hemorrhages, exudates, and neovascularization. Big datasets used for training CNN-based models for classification were also prepared. These datasets will contain labelled images with all the stages of DR, ranging from the very mild to the very severe. Several architectures of CNN can be used to recognize DR cases automatically; this approach may depend on the size of the dataset, the type of resources for computations, and the degree of desired accuracy. Deep learning techniques using CNNs like AlexNet, VGG, MobileNet, and Vision Transformers are the most significant progress to identify diabetic retinopathy from images of the fundus. The amount of choice in architecture depends on the size of the dataset, the quantity of resources required for computations, and the requirement for the deployment in real-time. Adam and gradient descent are optimisation algorithms. One of the optimisation algorithms is more preferred over the other based on a higher convergence rate, we would see in our ahead work which works best. The deep learning-based models may usher in a new revolution in early diabetic retinopathy detection and management with large datasets and transfer learning techniques. The performance of such CNN models, for instance, diabetic retinopathy detection models, will hugely depend on the optimization algorithm used. In training a network, the optimization algorithm is responsible for changing the weights of the network to minimize the loss function.

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