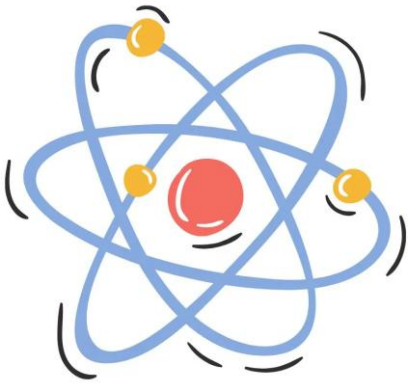

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IDENTIFICATION OF GLAUCOMA FROM FUNDUS IMAGES AND USING DEEP LEARNING TECHNIQUES

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Abstract: *The Retinopathy, often known as diabetic retinopathy (DR), is a common consequence of diabetes that can have an impact on a person's vision. If it is not identified at an early stage, it can result in blindness. Unfortunately, diabetic retinopathy is not a process that can be reversed, and treatment can only keep vision intact. Detection and treatment of diabetic retinopathy (DR) at an early stage can dramatically reduce the vision loss risk. The manual diagnostic procedure of the DR retinal fundus photographs by ophthalmologists is time consuming, difficult, and expensive. Additionally, it is possible to make an incorrect diagnosis. In recent years, deep learning has emerged as one of the most popular methods, and it has demonstrated improved performance in a variety of domains, particularly in the field of medical picture analysis and classification. Proposed Model uses DenseNet network for the purpose to classify and diagnosis of the diabetic retinopathy. These networks are widely utilized deep learning method in the field of medical image analysis, and they are extremely efficient. Performance of proposed model is evaluated by using Accuracy in training, learning rate, training loss, validation loss, validation accuracy, precision, recall, and sensitivity*

Keywords: *Machine Learning, Deep Learning, Glaucoma, optical coherence tomography, CNN, DR, Dense Net121*

1. Introduction

Diabetes is a disease that causes a lot of problems because it makes it hard to use glucose. In Type 1 diabetes the presence of insulin goes down which means pancreas is not able to make the insulin in this the person suffers sickness and fatigue. Type 2 diabetes can cause damage to the blood vessel at back side of an eye, which is known as diabetic retinopathy (DR).The International Diabetes Federation (IDF) says that there almost 463 million people suffered by diabetes in the world. Medical experts divide the level of intensity of DR into five separate stages [1]. There is no proof of any DR, no matter how mild, reasonable, severe, or proliferative it is, as shown by cases in fundus pictures or fundus images. It is thought that micro aneurysms, exudates, or bleeding seen on these retinal fundus scans are all signs of diabetic retinopathy (DR) [2]. Also, "revascularization" means the arrangement of abnormal blood vessels, which happens in the later stages of diabetic retinopathy (DR). In its early stages, DR can be successfully managed. However, if it is discovered later on, it could cause permanent loss of vision [3]. To diagnose the DR soon, ophthalmologists always advise that the diabetic person must undergo for a regular medical fundus screening. However, the retinopathy occurred by the diabetes which is not usually detect (usually caused a case of vision loss) until the significant damage of the fundus of the person's eye which leads an Adequate identification/ classification of DR scene that will help the ophthalmologists which determine the approximate measured intervention [4]. Diabetic patients around the world need normal screening methods for early discovery, which helps in rapid treatment.

Some first world countries proposed a well-structured screening system to provide effective and efficient supervision of diseases and provide accurate value and timely

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conduct respectively. Adequate identification helps in DR and after that physicians determine appropriate interference measures so that prompt treatment can be implemented speedily [5].

Unfortunately, the medical community has to find other ways to classify DR because it costs a lot to run these programs or there aren't enough qualified healthcare professionals. In addition, less residential countries are trying to reduce cost of classifying DR. The use of automatic computer methods connecting artificial intelligence is currently the most advanced method of solving this problem Artificial intelligence (AI) is replication of human aptitude using complex algorithms for machines, where the algorithm learns to distinguish patterns in data or then predicts / detects patterns in invisible data [6].

Mobile device-based retinal imaging requires one hour to give economical, faster, or more intelligent point-of-care (POCT) expertise for screening. This is because the number of people using smartphone-based knowledge is growing. Developing treatment plans for patients will be made easier with the utilization of mobile technology screening to categorize DR stages. This will result in a reduction in the burden of global illness or the provision of instruments that are both convenient and economical [7]. An evaluation of the presentation of retinal imaging using smartphones in the population under investigation has been included in some recent revisions. After that, patients who are considered to be at a high risk are linked to an appropriate medical center for treatment. Smartphone-based automated screening techniques become a significant springboard for effective DR management as the percentage of patients who are screened for treatment is less than five percent [8]. The application of artificial intelligence (AI) based on smartphones has been the subject of a number of research in the past, with the goal of determining the severity of diabetic retinopathy. It is vital to develop alternatives because mobile devices have a low memory capacity or computational efficiency, or because the majority of the most advanced exploratory work uses designs that are demanding, heavy, or computable. For the purpose of this investigation, we endeavored to achieve the absolute objective to develop a motion-based organization for the classification of retinal fundus photographs concerning their severity [9]. The plan makes use of a MobileNetV2 architecture that is both more capable and less significant than its predecessor, MobileNetV1. This architecture is better known for its presentation than its predecessor, MobileNetV1, and it does so without disrupting the primary essential characteristics of the development model, specifically. On a convention dataset, which is a composite of three datasets that are easily accessible for retinal fundus imaging, we qualified or tested a model that had low latency[10] or boosted competence. EyePACS [11], the Kaggle APTOS dataset [12], or the Messidor dataset are all examples. In order to achieve a good output, we either modify the hyperparameters or apply biologically activated retinal filters

1.1 . Background

Understanding diabetic retinopathy (DR), its source or transform in retinal characteristics is essential to building a good simulated intelligence system for selection. Retinopathy caused by diabetes is a condition that develops over time in diabetic people. The chronic disease known as diabetes mellitus (DM), which is more commonly referred to as diabetes, is characterized by persistently elevated blood sugar levels. The uncontrolled progression of diabetes can result in a number of chronic conditions, including diabetic foot disease, diabetic nephropathy, and diabetic retinopathy, among others. Diabetic retinopathy (DR is a problem that can be repaired without haste, and it is anticipated that it will affect around 191 million people by the year 2030 [13]. A blood sugar level that is too high might cause damage to the blood vessels that supply the retina, as well as cause permanent damage. To cope with this type of injure, body will produce new blood vessels to maintain nutrients,

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and these nutrientsor easily lead to leakage or bleeding. This can lead to medical conditions such as blurred apparition, or in some severe luggage it can lead to apparition loss [14].

1.2 Diabetic Retinopathy Stages Classifications

The doctor notes the process of DR by identifying the symptoms. Figure 1 shows a retinal imaging sample with a typical DR lesion with manual markings.

Hard exudates: In the Hard exudates retinopathy which defines the DR. In this the regularly appearance in the retinal image are looking like small yellowish and white spots with sharp edges [15].
Soft exudates: In the Soft exudates, also known as cotton-like spots, materialize white spots with fuzzy edges [16]. Exudate, include soft exudate or hard exudate, is one of mainly general early lesions of DR [17].

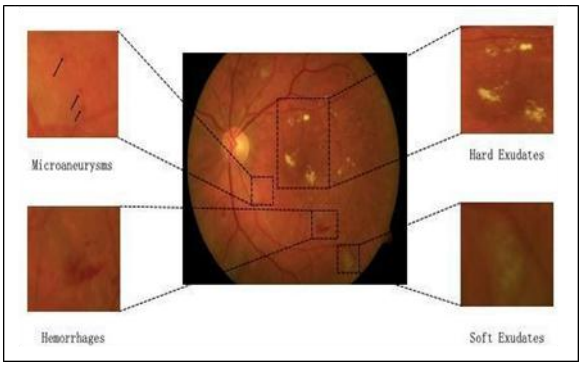

Figure 1: A Well Annotated Image ShowingLesions of Diabetic Retinopathy.

Microaneurysms: Microaneurysms are original clinically observable symbols by the non-proliferative diabetic retinopathy (NPDR) source through dilation of small blood vessels. Microaneurysms typically emerge as clusters of little red points with jagged edges with a range of 20 to 200 microns.

Bleeding: When microaneurysms burst in deep deposit of retina, then bleeding occurs. The United Kingdom, National Health System (NHS) is a overly support health classification. They have developed Diabetes Eye Screening Program (DESP). They used it to grade retinal fundus images; frequently up to 3 people It is mandatory to provide class. These classifiers must adhere to NHS DESP superiority promise standards one must be able to evaluate imagery to conclude severity of disease. They must uses these levels for the generation of a "final level" for every eye based on maximum level of difficulty experiential. The stages of DR can be confidential according to company of clinical facial appearance. The widely use of DR altitudes are distinct in below mentioned Table 1 in the following table 1

Table 1 The Stages of DR [19].

	Description
R0	**No detection of DR**
R1	**Mild symptoms of DR**

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R2	**Moderate symptoms of DR**
R3	**High symptoms of DR**

Figure 2 shows various stages of diabetic retinopathy on the basis of UKequivalent scale. The Normal fundus took place in R0. The stages distinguished by micro-aneurysms are Mild proliferative and severe proliferative. In severe proliferativeblood vessels are rotated around the retina which results in swelling and deficiency in the flow of blood capacity In the UKequivalent scheme, says that the mild DR stays in the R1 stage respectively.

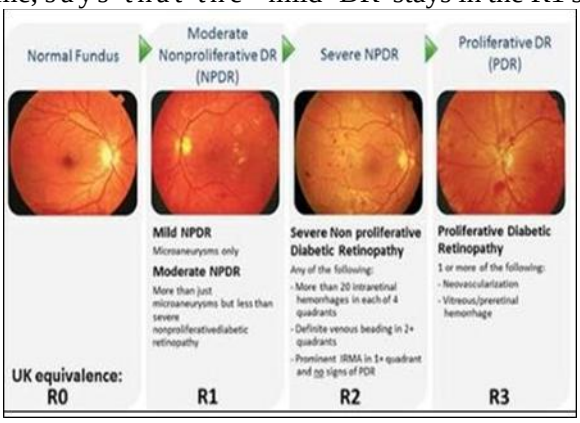

Figure 2: UK Equivalence showing the stages of Diabetic Retinopathy Stages

This corresponds to R2 in UK equivalent standard says that R2 stage shows the moderate stage of DR. Proliferative diabetic retinopathy is distinguished by vitreous hemorrhage or formation of new blood vessels which are more prone to bleeding or leakage. They correspond to R3 step in British equivalent standard.

3. Proposed Work

The proposed flow diagram begins with the input of diabeticretinopathy dataset from Kaggle, consisting of images in .jpg or .png format. These images undergo preprocessing, which includes image resizing and noise filtering to enhance data quality. The pre-processed data is divided into test and test data (80% for the training stage and 20% for the testing stage) to facilitate model evaluation and prediction. The classification phase uses the deep learning algorithms, particularly. DenseNet to categorize retinal images into relevant classes. The ultimate objective is to classify images as depicting either diabetic retinopathy or non-diabetic retinopathy basedon dataset attributes. A critical step involves the comparisonof the results obtained from both algorithms, determining theefficiency of each. Performance estimation follows, assessing key metrics such as accuracy, precision, recall.

3.1 Pre-processing

Pre-processing basically a important step for the preparation of the raw data for analysis. In this context, it includes several steps to transforminput images into a suitable format for training the deep learning model. The main pre-processing techniques used here are:

1. **Resizing**: Adjusting the size of an image to a fixed dimension (224x224 pixels) to ensure uniformity across the dataset.

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2. **Cropping**: Extracting a region of interest from animage to focus on a specific area, which can help in removing unwanted background details?

3. **Rotating**: Adjusting the orientation of an image by rotating it at specific angles (90 degrees clockwise, counter-clockwise, and 180 degrees) to augment the dataset with various perspectives.

4. **Flipping and Brightness Adjustment**: Additional augmentations like horizontal/vertical flipping and brightness adjustments to maximize the variety of that train dataset.

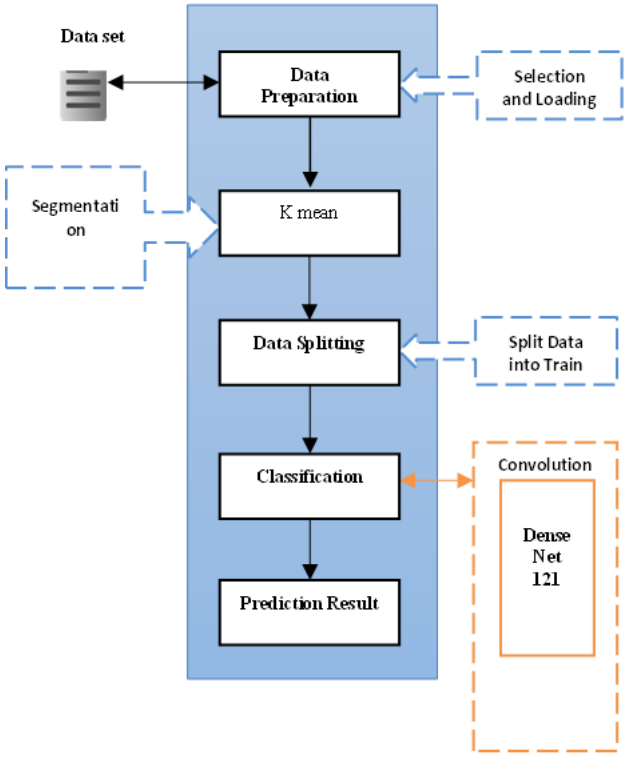

Figure 3 : Proposed Flow Diagram

3.2 Image Augmentation

Image augmentation is the process of generating new training samples by applying random transformations to the existing images. The model more robust and generalizable by exposing it to a variety of image variations during training.

3.3 Loading and Displaying Data

The dataset is loaded from a specified directory containing subfolders for each category (e.g., glaucoma and normal). The images are displayed to verify proper loading and visual inspection of the data. This step also includes gathering information about image dimensions to standardize them.

3.4 Dataset Preparation

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After loading, images are resized and normalized (scaled to the range [0, 1]) to ensure consistent input for the model. Labels assigned on the basis according to the category of each image.

3.5 Dataset

We are using the Glaucoma Detection Dataset from Kaggle The Dataset used in the proposed model contains the images which are unaffected by glaucoma and glaucoma affected images. This data set contains images/oct scans of the eye. This dataset contain total of glaucoma affected images and normal images.

3.6 Segmentation

We are using K means for clustering to classify similar images and discover patterns in it and minimize the distance between two clusters.

Train-Test Split

The dataset is divided into train and test datasets using an 80- 20 ratio. The training dataset is generally uses for the training of the model, while in the testing phase test dataset is generally uses for the evaluation of the respective performance.

Model Building

The DenseNet121 model, pre-trained on ImageNet dataset, is used for feature extraction. Additional layers are added on top of DenseNet121 to adapt it for binary classification (glaucoma vs. normal). The Dense Net 121 architecture with layers as seen in Figure 4.

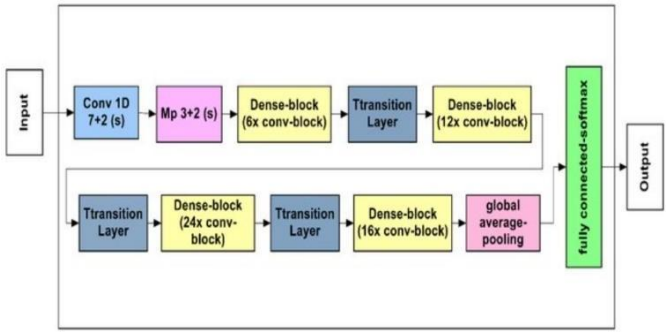

Figure 4: DenseNet121 Architecture

DenseNet121 Architecture consist of :

- **Conv2D Layer**: A convolutional layer to process theinput images.
- **GlobalAveragePooling2D**: A pooling layer to reduce the dimensionality problem of feature maps.
- **BatchNormalization**: Normalizes the output of theprevious layers to improve training stability.
- **Dropout**: A regularization technique to preventoverfitting by dropping random

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neurons at the training phase.

- **Dense Layer:** All neurons are fully connected with each layers by the ReLUactivation for learning complex patterns.
- **Output Layer:** A softmax layer for binaryclassification.

- **Model Training**

This model uses the binary cross-entropy loss and the Adam optimizer. It trained according to trained dataset on a specific iteration of epochs, and the training history (accuracy and loss) is recorded and plotted.

- **Prediction:**

This module is responsible for applying the trained models to the test dataset, predicting the classes of retinal images based on the learned features. It assesses the generalization capability of that particular model to new or we can say unseen data.

- **Result Generation**:

The result generation module compiles the outcomes of the classification and prediction stages. It includes the generation of performance metrics such as precision, accuracy, ROC curves, recall, error rates and confusion matrices. The results are crucial for evaluating the effectiveness and efficiency of the implemented deep learning models.

3. Simulation Result

In the result discussion for that propose model implemented in Python, it is crucial for the assess of the performance of the deep learning algorithms. Input dataset images shown in Figure 5. DenseNet in classifying diabetic retinopathy images. The evaluation parameters gives insights for the efficiency and accuracy of that models. Input images transformed from its original image to resized image the it is converted into gray scale image shown in Figure 6-8

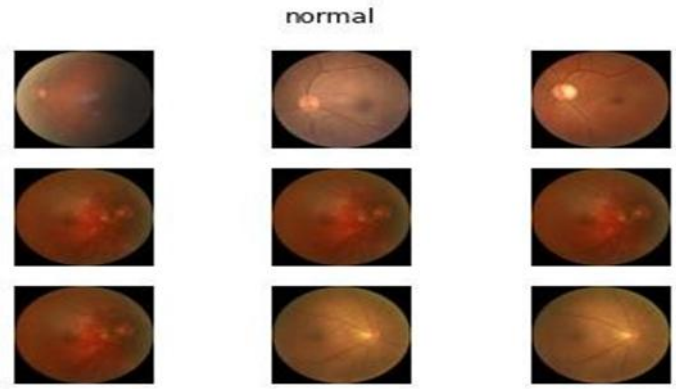

Figure 5: Dataset Images

Firstly accuracy metric indicates the overall correctness of the classification. It calculated the ratio of the correct predicted instances to the total instances. The representation of image pixels is shown in histogram format show in Figure 9. Recall, Precision and the F1 score are important metrics, especially in medical image classification tasks. Precision is the ratio of true positives and the sum of false

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positives and true positive, reflecting the model's capacity to correctly identify positive cases. Recall, on the other hand, isthe ratio of true positives and the sum of true positives and false negatives, measuring the model's capacity to capture every positive result. The classification of Loss and Accuracy shown in the Figure 10. F1 score is generally the harmonic meanof the precision and recall, which are providing a balanced evaluation of the model's performance.

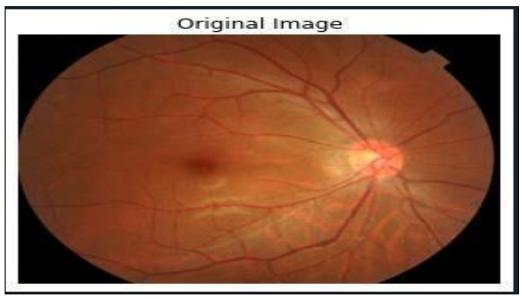

Figure 6 : Original Image

Figure 6: Original Image

Figure 7 : Resized Image

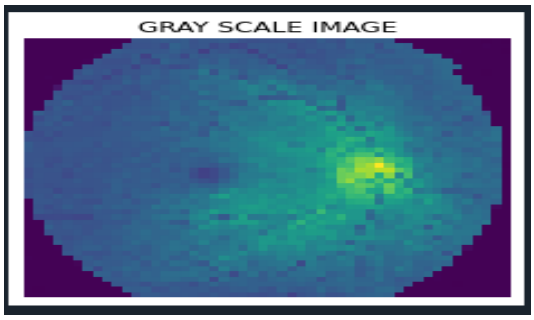

Figure 8 : Gray Scale Image

In this simulation, a deep learning model for image classification is implemented using TensorFlow and Keras. That model architecture contains max-pooling layers, convolutional layers, dropout layers, and dense layers to effectively learn to classify images. Adam optimizer isutilized for model optimization. The dataset, obtained from Kaggle, comprises images of diabetic retinopathy. The images undergo preprocessing, including resizing and noisefiltering, before being divided into train and test datasets.

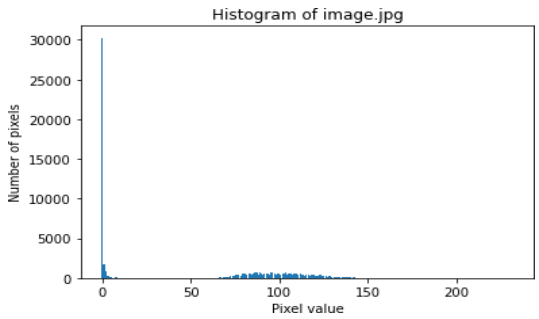

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Figure 9 : Histogram Image

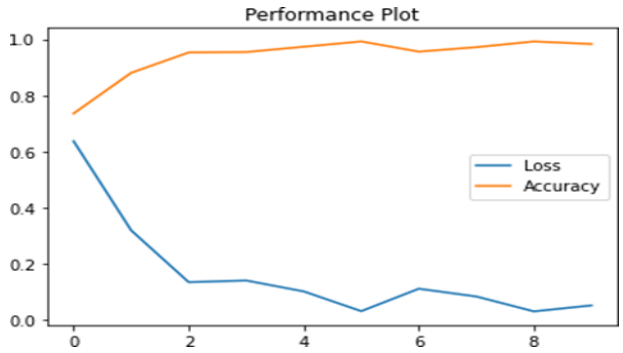

Figure 10: Classification Loss and Accuracy

Label Binarizer is employed to convert categorical labels into binary vectors. The model is trained on the training set and evaluated on testing set. The simulation includes the use of matplotlib for visualizing performance metrics, includes accuracy and loss, during the training process. Additionally, the scikit- learn library is utilized for generating a classification report, offering insights into the model's F1-score, Precision and Recall. The final implementation integrates various libraries and techniques, including TensorFlow, Keras, scikit-learn, and matplotlib, to develop and evaluate an efficient deep learning model for diabetic retinopathy classification. Table 2 represent Classification Report of Proposed Model. Figure 12 represent glaucoma image as classified by proposed model.

Table 2: Classification Report

	precision	recall	f1-score	support
glaucoma	0.97	0.96	0.97	**156**
normal	0.97	0.98	0.97	**176**
accuracy			0.97	**332**
macro avg	0.97	0.97	0.97	**332**
weighted avg	**0.97**	**0.97**	**0.97**	**332**

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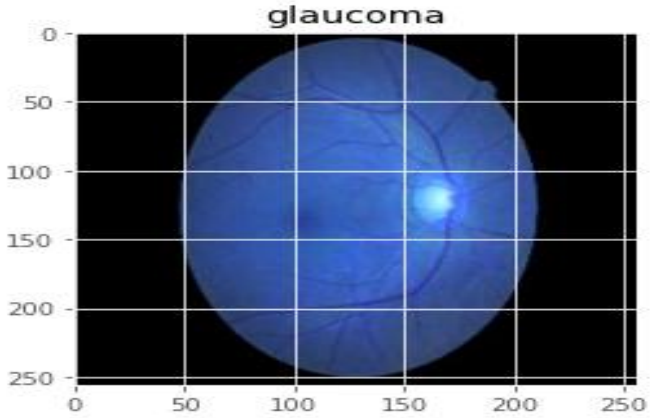

Figure 12: Classification Output of a Glaucoma image Size of 65 X 65

Table 3 presents a comparative analysis demonstrating that the proposed model achieves high accuracy while maintaining a lightweight architecture.

Table 3: Comparison Table with Existing Work

S.NO.	Author's Name	Technique And method	Result
1	YvesAttry, Kalin, et.al. (2022)	MobileNetV2, DenseNet121, InceptionV3, InceptionResNetV2, ResNet50, and VGG16,	**88.56% accuracy**
2	D.Shamiaet al (2022)	DCNN, SVM, Back Propagation, Random Forest ,KNN	**91% for DR, 90% for cataract *86% for glaucoma***
3	Hongyong Zhang et. al. (2019)	Alginate hydrogel microbeads, 3D Cell cultivation, HEPES buffer solution (pH 7.1)	**91% accuracy**
4	Chaodong Ling et. al. *(2019)*	DRIVE, STARE, and FIRE data sets, Markov model in waveletdomain	**85% accuracy**
5	Weingart, Mircea, et. al.(2019)	KSVD and BM3D methods,e ARIA and B- COSFIRE filtersmethods	**87.79%accuracy**
6	Behnam Azimi et al. (2020)	age-related macular degeneration (AMD), fully convoluional networks (FCNs), graphshortest path	**sensitivity 87.38% , NSGC81.10%, KGC 75.69%, GC 70.11%,**
7	Jelena Novoselet. al.(2017)	Loosely coupledlevel sets, central serous retinopathy, diabetic-macular edema	**88% accuracy**
8	Jie Wang et. al. (2021)	Disentangled Reconstruction Neural Network (DRNN), Feature disentanglement, Retina vessel segmentation,	**90.82% accuracy**

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9	Existing	Transfer Learning Approach for DR Detection by using(RESNET-50)	**89.4% accuracy**
10	**Our Proposed work**	**DenseNet 121**	**97% accuracy**

4. Conclusions

In this study, we successfully achieved significant results inthe Diabetic Retinopathy (DR) intensity classification system by leveraging datasets subjected to pre-processing techniques such as image enhancement. Our model incorporatesthe computationally efficient architectures of DenseNet bothrenowned for their speed and computational efficiency. To validate the universality of our model, we conducted tests with unseen data, demonstrating its robust performance across different datasets

The outcomes of our experiments shows that our model performed exceptionally well, attributing its success to the various methods employed at each stage of the Machine Learning (ML) extraction pipeline. Looking forward, our future endeavors involve deploying and testing this model on high-end smartphones to assess its efficacy as an instant diagnostic tool for accurate and rapid DR classification.

Our literature review encompassed an exploration of trends connected towards the artificial intelligence in diabetic retinopathy detection. We specifically examined the behavior of lightweight architectures and compared them with other established models. The empirical testing substantiated the effectiveness of the lightweight architecture, showcasing comparable results while boasting advantages in terms of speed cost effectiveness, computational, speed. In our experiments, we achieved an impressive 90% accuracy in tests with previously unseen data. The utilization of the DenseNet model architectures contributed to the overall stellar performance of our model.

5. Future Research Directions

Many future guidelines can be enumerated for the benefit ofresearch society, or explain as follows:

Improve existing models: existing models can be optimized by adjusting various hyperparameters, or can be improved by various preparation techniques. This helps to build a model that is more efficient than existing arrangement. Improving model to have good generalizations is key to a satisfactory in deep learning model.

Build an Android app or test it in the clinical world: We can test effectiveness of model by integrating it into the androidapp, so that we can test the real patients in the clinical world marina. This will provide a better understanding of the effectiveness of such a system in the clinical setting.

Additional research: MobileNetV2 is used because of its lightweight architecture, speed or computational competence, it is worth conducting a proportional study of

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models based on these standards in future work. Some possible extensions of our research work are listed below:

Optimizing the CNN architecture: We proposed a novel MobileNet-Dense model which is constructed using 4 dense modules as the default setting. A shallower MobileNet- Dense model (e.g., a MobileNet-Dense model with 3 dense modules) may achieve similar performance with fewer MAdds and Parameters or a deeper MobileNet-Dense model may achieve noticeably better performance at an acceptable cost.

Pruning the trained model: Another possible extension of our work would be further improving the computational efficiency of our DR classification system by pruning and retraining the trained MobileNet-Dense model andMobileNetV2 model (removing the convolution filters in convolutional layer or weights in fully connected layers which are less correlated to the final results) as it has been shown that network pruning and retraining reduce the number of MAdds and Parameters of the model while maintaining similar performance in various applications or benchmark datasets.

Enhancing the image contrast: the EyePACS dataset contains some poorly exposed images. It would be interesting to investigate whether the overall classification performances of our system could be significantly improvedby enhancing the image contrast using adaptive histogram equalization algorithm or contrast limited adaptive histogram equalization algorithm.

Stacking Mobile Net-Dense with different CNN models: As both MobileNetV2 and Mobile Net-Dense use the depth wise separable convolutional layer as the basic building block and these two models achieve similar performance onboth Eye PACS dataset and Messidor database. Thus the features extracted from these two models might be highly correlated which results in limited improvement when performing ensemble learning. It would be interesting to investigate whether we can enhance the performance of the DR classification system by stacking the Mobile Net-Dense model with other types of computationally efficient CNN models which are not constructed using depth wise separableconvolutional layers.

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