Development of a Computer-Aided Diagnostic System for Diabetic Retinoscopy

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Introduction

Introduction

- Diabetic retinopathy (DR) is one of the micro vascular complications that affect 1 out of 3 patients with diabetes mellitus (DM) [1]
- High blood sugar levels damage blood vessels in the retina, leading to various eye problems.
- Symptoms may include blurred vision, floaters, difficulty seeing at night, and eventually vision loss if left untreated
- DR risk in DM patients increases with the duration of the disease;therefore, early diagnosis and treatment are critical to prevent the unwanted final outcome of blindness [2]

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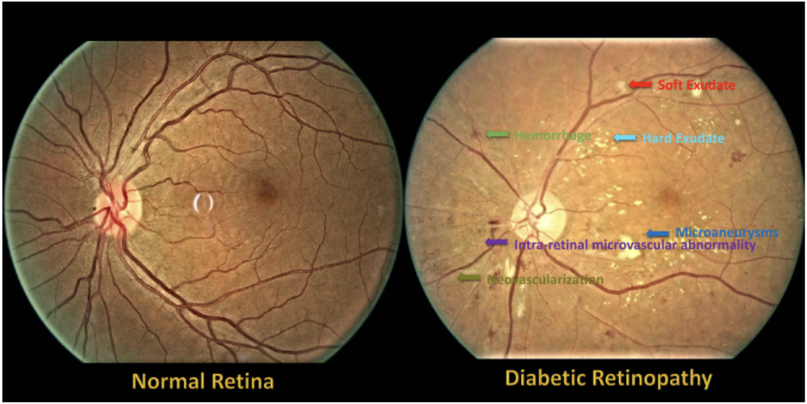
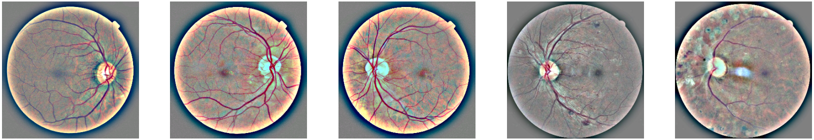


Figure 1: Illustration of DR retina

Stages of DR



No DR | Mild DR | Moderate DR | Severe DR | Proliferate DR

Figure 2: Stages of DR

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Applications

- Early detection of severity of DR
- Assisting healthcare professionals in making informed decisions
- Prioritizing patients for timely interventions
- Monitoring disease progression over time

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Motivation

- Early intervention can prevent vision loss
- Limited availability of eye care specialists
- Remote monitoring of DR
- Improved data sharing and collaboration

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Basic Architecture

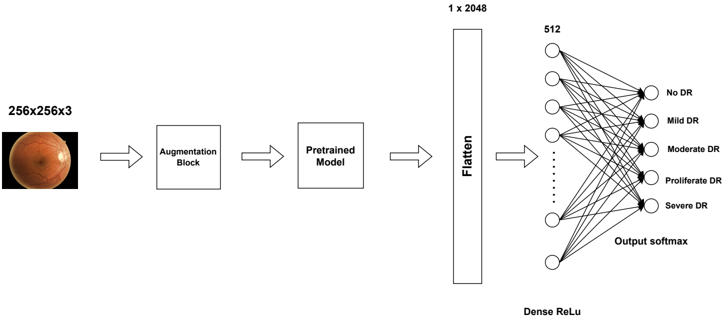

Figure 3: Basic Architecture of automated DR detection model

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Related Work

Literature Survey

S. No.	References	Methods	Dataset	Performance		
				specificity(%)	sensitivity(%)	accuracy(%)
1	Ghosh et al.[3]	CNN	EyePACS	-	85.2	85
2	Revathy R. et al.[4]	SVM+KNN	Kaggle	-	-	82
3	Carrera E. et al.[5]	SVM + Decision Tree	Messidor	97	-	92
4	Pradeep J. et al.[6]	Segmentaion + CNN + SVM	EyePACS	-		95
5	Srivastava et al.[7]	Inception + SVM	EyePACS	90.2	80.2	87.7

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S. No.	References	Methods	Dataset	Performance		
				specificity(%)	sensitivity(%)	accuracy(%)
6	Taufiqurrah - man et al[8].	MobileNetV2-SVM	Kaggle APTOS	-	-	85
7	Li et al.[9]	Vgg-s + SVM	Messidor	97.11	86.03	92.01
8	Xiao et al.[10]	SE-MIDNet	DRD	97.6	99.43	88.24
9	Chen P. et al.[11]	2 staged NAS-Net + SMOTE	EyePACS	85	84	86
10	M. Shorfuzza-man et al.[12]	DenseNet121+ Resnet+ Inception Net	APTOS	-	94	96.2

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S. No.	References	Methods	Dataset	Performance		
				specificity(%)	sensitivity(%)	accuracy(%)
11	Li et al.[13]	Cross attention Network	Messidor	-	92	92.6
12	Hi et al.[14]	DenseNet-121+ Category Attention Block	Messidor	-	-	84.08
13	AbdelMaksoud et al.[15]	E-DenseNet	EyePACS	72	98.3	96.8
14	Tymchenko B et al.[16]	EfficientNet-B4+EfficientNet-B5+SE-ResNeXt50t	Messidor, Idrid	98	84	92
15	Qian et al. [17]	AD2Net	Kaggle Eye-PACS	-	-	83.2

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S. No.	References	Methods	Dataset	Performance		
				specificity(%)	sensitivity(%)	accuracy(%)
16 17	Chetoui M. et al[18].	FL + Vision Transformer	APTOS	95	95	95
18	Gu et al. [19]	Vit + CSRA	IDRID	82.45	81.40	82.23
19	Dihin R et al.[20]	Multi Wavelet+Swin Transformer	APTOS	80.17	46.26	82
20	Yang Y et al.[21]	ViT-Large +MAE	Messidor2, APTOS, EyePacs	92.63	97.3	92.6

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Issues

- Current deep learning models for DR are resource-intensive and impractical in limited-resource settings.
- Distinguishing between mild and moderate cases is challenging due to subtle image feature differences, requiring better feature extraction methods.
- Large Vision Models(LVMs) trained on one dataset struggle to generalize to others effectively.
- DR datasets have significant class imbalances, with fewer images of severe cases compared to lower severity classes.

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Objectives

- Addressing class imbalances through data augmentation to generate synthetic samples for underrepresented severe and proliferative cases.
- Selecting and optimizing computationally efficient deep learning models with low resource requirements to enable accessible deployment in resource-constrained healthcare settings.

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Experimental Results

Experimental Results

- Utilized the DR dataset from Kaggle, consisting of preprocessed images from Messidor and EyePAC.
- Applied EfficientNetv7 architecture for classification, achieving an accuracy of 60%
- The dataset was split into 80% training and 20% validation sets for model training and evaluation.
- For testing, utilized a dataset from Kaggle containing 25,000 images with class imbalances.
- Randomly sampled 150 images from each class for a more balanced evaluation.

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Preprocessing

- The classes are balanced through under-sampling the majority class i.e. the normal class.
- All classes have been cropped and resized to 256 x 256, to speed up training and avoid unnecessary computation resources for preprocessing.
- Images are subjected to Contrast Limited Adaptive Histogram Equalization (CLAHE) with threshold 2.0 for better feature differentiation.
- Finally, data augmentation by means of horizontal flipping, rotation and zooming is carried out to upsample the classes and avoid overfitting.

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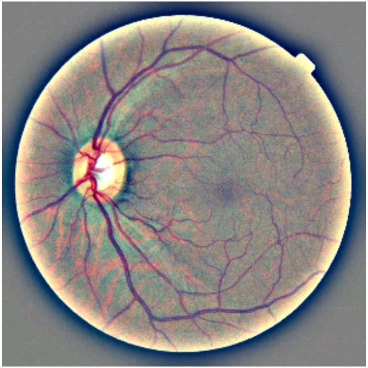

Figure 4: Before Pre-processing

Figure 5: After Pre-processing

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Hyperparameters

Table 1: The DR model training hyperparameters.

Hyperparameters	**Valor**
Optimizing function	ADAM optimizer
Epochs	30
Batch size	32
Initial learning rate	1×10^{-2}
Dropout	0
Classifier	0.01
Number of classes	5 classes

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Results on EfficientNetB7

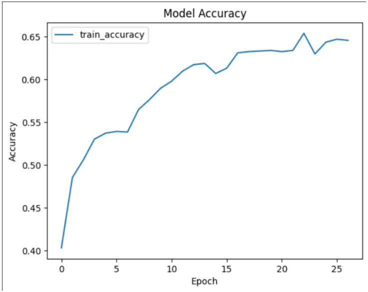

Figure 6: Model Accuracy of EfficientNet

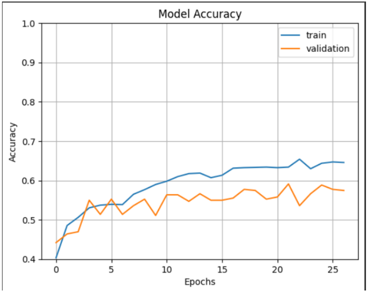

Figure 7: Train vs Validation Accuracy of EfficientNet

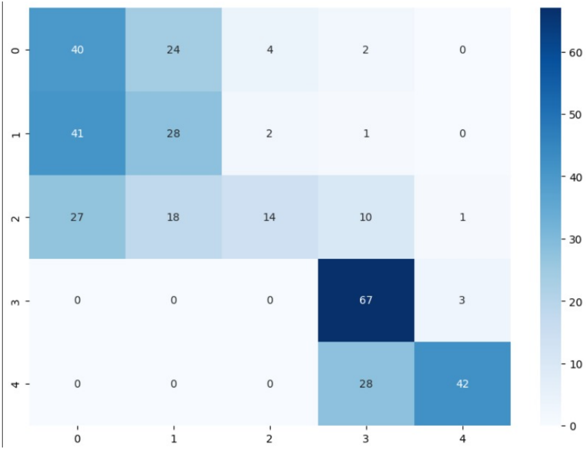

Figure 8: Confusion Matrix of EfficientNet

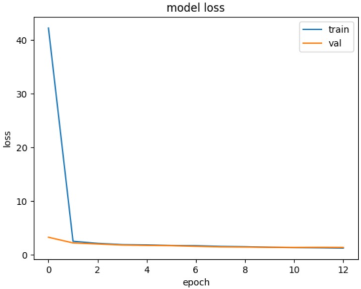

Figure 9: Model Loss of ResNet50

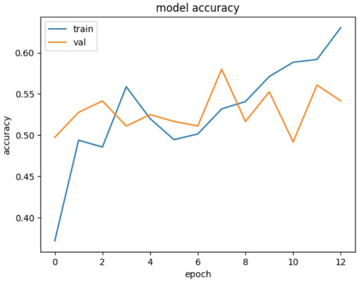

Figure 10: Model Accuracy of ResNet50

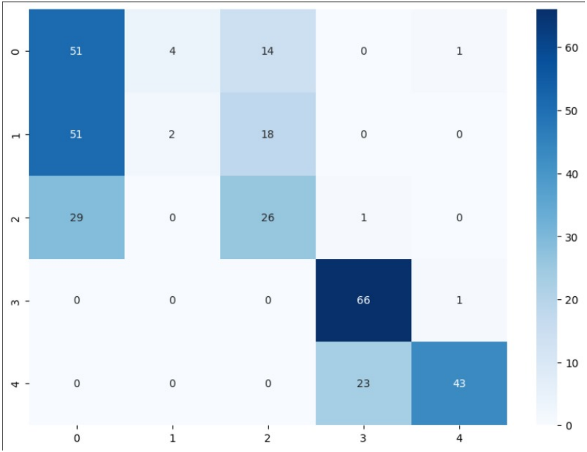

Figure 11: Confusion Matrix of ResNet50

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Results

Method	Sensitivity	Specificity	Accuracy	Top2 Accuracy
EfficientNetB7	60	88.90	55	80.12
ResNet50	57.15	89.22	56	82

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