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ISSN2249-3352(P) 2278-0505(E)

CosmosImpactFactor-5.86

# CLASSIFICATION OF DIABETIC RETINOPATHY DISEASE LEVELS BY EXTRACTING TOPOLOGICAL FEATURES USING GRAPH NEURAL NETWORKS

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## ABSTRACT

Diabetic Retinopathy is the most common eye disease that diabetes can cause. It can even result in vision loss and complete blindness. Early detection prevents complete vision loss. However, it is challenging to detect it early because it may not show symptoms in the early stages. The existing models for diabetic retinopathy cannot detect all the stages of diabetic retinopathy. The most widely used metrics like accuracy, f1-score, precision, and recall; do not

consider the level of disagreement between labels, which helps in detecting all the stages of diabetic retinopathy. This paper used ResNet, VGG, and EfficientNet pre-trained models. We performed results evaluation using quadratic weighted kappa, which is appropriate for classifying different stages of diabetic retinopathy based on the severity. Furthermore, it considers the level of disagreement between actual and predicted labels. We have achieved the quadratic weighted kappa score of 0.85 using the EfficientNet b3 network, surpassing the

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Mar2025, Volume 15, ISSUE 1

UGC Approved Journal



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ISSN2249-3352(P) 2278-0505(E)

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existing models like support vector machines, decision trees, convolutional neural networks, and DenseNet pre-trained model.

## 1.INTRODUCTION

**DIABETIC RETINOPATHY** is the most common diabetic eye disease and a leading cause of blindness in American adults [1]. Because of the excessive blood sugar, the tiny blood vessels in the retina will be broken and lead to hemorrhages in the retina, and this will cause diabetic retinopathy. Any diabetes can result in diabetic retinopathy. The longer one has diabetes, the higher the risk of diabetic retinopathy. Depending on the severity of the disease, the effect can be in the range of near-normal vision to complete loss of sight. [2], [3]. Diabetic Retinopathy is more likely to attack adults over 40 who have diabetes. In the United States of America, approximately 4.1 million US adults suffer from diabetic retinopathy [4]. Early detection of diabetic retinopathy can prevent 95% vision loss. This work was supported in part by NSF under Grant CNS-2117785. Ch. S. Venkatesh is with the School of Computing

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[5]. Diabetic Retinopathy may not give any symptoms in the earlier stages as it happens inside the eye, even when the blood sugar level is maintained and vision is very normal. Because of this, the doctor can only detect diabetic retinopathy after proper examination [6]. Diabetic Retinopathy can be divided into two stages: NonProliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The NPDR can further be divided into three phases: Mild, Moderate and Severe [3], [7]. NPDR is due to excessive sugar levels that



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ISSN2249-3352(P) 2278-0505(E)

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start affecting the tiny blood vessels in the retina, which leads blood vessels to become more swollen and leak fluid; as a result, the retina lacks oxygen and nutrients [3], [8]. As a result, the body produces a vascular endothelial growth factor (VEGF) to provide nutrients and oxygen to the eye's retina. But these new cells are fragile and can be easily damaged, resulting in more swelling and leaking. This advanced stage is called Proliferative Diabetic Retinopathy (PDR) which is hazardous as it often causes permanent vision loss [3], [9]. Using the PyTorch framework, we developed VGG, ResNet, and EfficientNet pre-trained models and fine-tuned them to suit diabetic retinopathy detection. PyTorch supports automatic differentiation and efficiently uses GPUs for parallel processing [10]. Furthermore, we used Google Colab Pro, which gives GPU run time for a limited time and RAM of 25.46 GB to train the developed models. As diabetic retinopathy, early detection can prevent the patients from vision loss. We have focused on the early detection of diabetic retinopathy using pre-trained models like ResNet, VGG, Efficient

Net. We have used the publicly available dataset from Kaggle [11] to develop the state-of the-art model for diabetic retinopathy detection. We first used VGG, followed by ResNet, and finally Efficient Net. We also have demonstrated the results of all the models using the most relevant metric known as Quadratic Weighted Kappa [12]. The EfficientNet b3 60 model has achieved a state-of-the-art QWK score of 0.85. The proposed model can be used in healthcare to aid the doctors in the decision-making on the patient's model as the model can distinguish each class of diabetic retinopathy.

## 2.LITERATURE SURVEY

Gulshan et al. [11] and Abramoff et al. [12] proposed a CNN model for automated screening of diabetic retinopathy. They trained deep neural networks using datasets of retinal fundus images. The CNN architecture consisted of multiple convolutional layers followed by max pooling layers to extract features from the images. The extracted features were then



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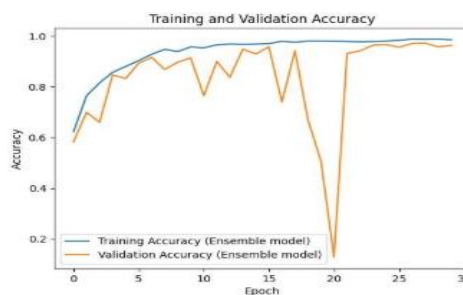
ISSN2249-3352(P) 2278-0505(E)

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passed through fully connected layers for classification. Gargeya and Leng [13] presented a review of deep learning-based approaches for diabetic retinopathy screening. They discussed different CNN architectures used in the literature, including AlexNet, GoogLeNet, and ResNet, for diabetic retinopathy detection. Li et al. [14] proposed a multi-task deep learning framework for simultaneous detection and grading of diabetic retinopathy lesions. Their model effectively detected lesions such as micro aneurysms, hemorrhages, and exudates while classifying diabetic retinopathy severity levels. Das et al. [15] proposed a transfer learning approach for diabetic retinopathy detection using CNN models pre-trained on natural image datasets. Their method showed promising results even with a limited number of diabetic retinopathy images. Burlina et al. [16] presented a deep learning model for detecting and classifying retinal lesions related to diabetic retinopathy. Their system incorporated multiple CNN architectures to handle different lesion types, improving overall performance. Rajalingappaa et al.

[17] introduced a deep learning model for diabetic retinopathy classification using retinal fundus images. Their approach utilized a combination of CNN and Long Short-Term Memory (LSTM) networks to capture spatial and temporal patterns. This research focuses on diabetic retinopathy classification using an ensemble of deep learning models, VGG16 and Inception V3, with a shared fully connected layer. Both models are pretrained on ImageNet, and specific layers were frozen to prevent overfitting and enable transfer learning. By leveraging the strengths of both architectures, and combined feature extraction aims to enhance accuracy in classifying diabetic retinopathy into five distinct categories

### 3. OUTPUTSCREENS



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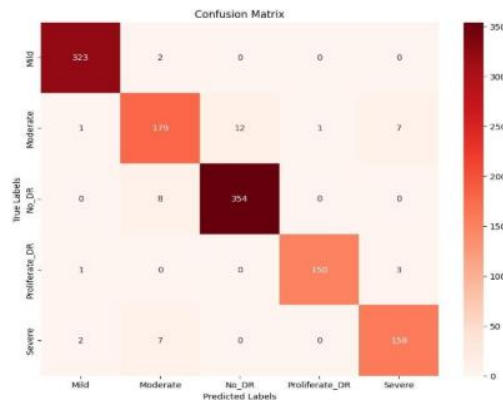
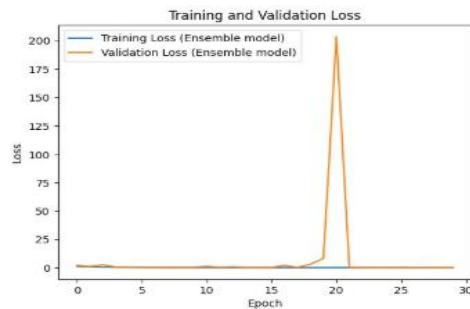
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## 4. CONCLUSION

Until now, little research has been done on detecting all the stages of diabetic retinopathy with higher Quadratic Weighted Kappa. In this paper, we have used the three pre-trained models ResNet, VGG, and EfficientNet. Among them, VGG and ResNet can only detect class 0 with a higher probability. Our results suggest that using pre-trained models like ResNet, VGG,

which are scaled only by their depth, cannot learn the features from the images that correspond to all the stages of diabetic retinopathy. Then, we found the EfficientNet models that use the compound scaling method uniformly scale the depth, width, and resolution. So, an efficient net model can detect more than 1 stage of diabetic retinopathy. The EfficientNet b3 model can detect all the stages of diabetic retinopathy with a higher quadratic weighted kappa score of 0.85. As, we have used the Google Colab Pro for model training, the resources are not sufficient to train the efficient net b7 model. However, we achieved the higher quadratic weighted kappa score of 0.85. There is still an improvement that can be done by using higher resolution images, using the ensemble of different CNN models, or the same model that achieved the best result. In our case, it is efficient net b3 and more advanced architectures like CoAtNet, which uses depth-wise convolution and self-attention can be used and check how it performs.

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Mar2025, Volume 15, ISSUE 1

UGC Approved Journal



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ISSN2249-3352(P) 2278-0505(E)

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## 5. REFERENCE

[1] Haykin, S. (2008). Neural Networks and Learning Machines. Pearson.

[2] Mondal, A., Ghosh, S., & Ghosh, A. (2017). Partially camouflaged object tracking using modified probabilistic neural network and fuzzy energy based active contour. International Journal of Computer Vision, 122, 116-148.

[3] Ross, T. J. (2004). Fuzzy Logic with Engineering Applications. Wiley.

[4] Dehuri, S., Ghosh, S., & Cho, S. (2011). Integration of swarm intelligence and artificial neural network. World Scientific, 78.

[5] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

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Mar2025, Volume 15, ISSUE 1

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