International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 11 Issue: 05 | May 2024 www.irjet.net p-ISSN: 2395-0072

HYPERPARAMETER-TUNED DENSENET121 FOR DIABETIC RETINOPATHY CLASSIFICATION: A DEEP LEARNING APPROACH

P. Saranya [1], Dr. C. Vennila[2]

[1] *Assistant Professor, Dept. of Computer Science & Engg., Government College of Engg. Srirangam, Tamilnadu, India*

[2] *Professor, Dept of Electronics & Communication Engg., Saranathan college of Engineering, Tamilnadu, India*

Abstract - *In this study, we employ a hyperparameter-tuned DenseNet121 architecture within a Convolutional Neural Network (CNN) framework to analyze fundus oculi images for predicting the presence and severity of Diabetic Retinopathy (DR). Diabetes, a condition characterized by elevated blood sugar levels, can lead to DR, a significant cause of vision impairment and blindness, especially among older individuals. Early detection of DR is crucial for timely intervention and treatment. Our model is trained and evaluated using a dataset comprising labeled fundus oculi images, each annotated with the severity of DR. Leveraging hyperparameter tuning, specifically optimizing the learning rate and dropout rate, we enhance the performance of the DenseNet121-based CNN model. Through rigorous experimentation, we demonstrate the effectiveness of our approach in accurately classifying DR severity levels, thus contributing to early diagnosis and management strategies for this sight-threatening condition.*

Key Words: Diabetic Retinopathy, Deep Learning, Convolutional Neural Network, Transfer Learning.

1.INTRODUCTION

Diabetic Retinopathy results from damage to the blood vessels in the retina caused by diabetes. Individuals with diabetes often experience some degree of retinal damage. The affected blood vessels can swell, leak, or promote the growth of new blood vessels. The loss of pericytes, which are contractile cells that envelop capillary endothelial cells in the body's venules, contributes to capillary damage. This damage occurs due to high levels of glucose in the blood, which clump together in the capillaries and impede blood flow, a condition known as ischemia. Microaneurysms, resulting from the diminished blood flow caused by the deterioration of these blood vessels, are saccular enlargements at the venous end of retinal capillaries. This process compromises the arteries' impermeability, leading to leaks such as bleeding or lipid exudation.

Ischemia in the retina leads to two major complications. The first issue involves the synthesis of the cytokine protein VEGF, which promotes the formation of new blood vessels (neovascularization) from existing ones. This protein can cause problems by proliferating on the surface of the vitreous humor and retina. Due to insufficient blood flow, these new vessels continue to grow until they rupture, leading to bleeding in the vitreous cavity or tearing the retina, ultimately resulting in vision loss due to tissue expansion. The second issue is plasma leakage, which involves lipid exudation that deposits fat in the macula, altering its structure and leading to vision impairment.

After examining the retina's fundus, diabetic retinopathy can be classified from its mildest to most severe stages. The two primary forms of the condition are Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is further divided into three subcategories: mild, moderate, and severe, as illustrated in Figure 1.

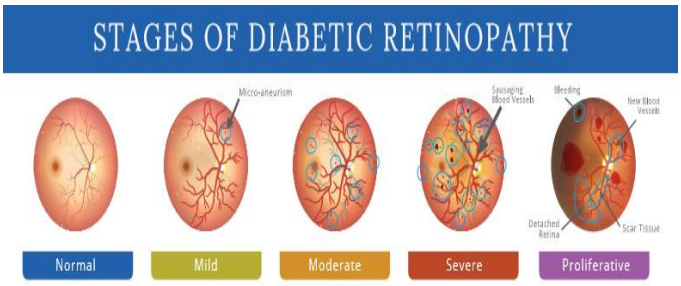

Fig-1: Stages of Diabetic Retinopathy

Deep learning (DL) is a well-established technique that automatically extracts features from images through a convolutional neural network's layer stack. These features enable the classification of image contents by identifying specific patterns. In this study, we propose a DL model to categorize retina fundus images and identify diabetic retinopathy (DR) across all stages. We utilize DenseNet121, a type of Convolutional Neural Network, to distinguish between healthy eyes and those affected by proliferative diabetic retinopathy.

2. RELATED WORKS

Numerous studies have explored the detection and classification of diabetic retinopathy (DR) using various methods. One of the pioneering works in this field is by Cree et al. [2], who developed a system that used hand-engineered features and empirically determined parameters to classify digitized retina fundus images.

Yun et al. [3] introduced a method for classifying retina fundus images into categories such as normal, moderate, severe, and proliferative diabetic retinopathy (DR). Their approach included preprocessing the images using morphological operations with disc and diamond structuring elements. Features were then extracted, focusing on pixel area, perimeter, and RGB channel analysis. Classification was carried out using a single-layer feed-forward neural network.

Rosas et al. [4] concentrated on the detection of microaneurysms in retinal images. Their approach involved applying computer vision techniques to preprocess the images, extracting features related to nonuniform lighting and grayscale intensities. Principal component analysis (PCA) and the radon transform were employed to distinguish round-shaped candidate regions and quantify discrete angle values, respectively.

Gargeya et al. [5] introduced an automated diabetic retinopathy (DR) screening system that achieved an impressive area under the curve (AUC) of 0.95 on the Messidor dataset using a 5-fold cross-validation technique. Their approach aimed to streamline the screening process by leveraging machine learning algorithms.

Chetoui et al. [6] devised a system for detecting referable diabetic retinopathy (DR) and vision-threatening DR by employing EfficientNet with transfer learning. Their work yielded promising outcomes, achieving an impressive area under the curve (AUC) of up to 0.98 on both the APTOS 2019 dataset and the EyePACS dataset.

Dondeti et al. [7] explored the use of pre-training model NASNET and T-SNE space for feature extraction in DR classification. Their approach, based on the APTOS 2019 dataset, achieved an accuracy rate of 77.90%.

Qummar et al. [8] presented an ensemble method employing five deep learning models, specifically crafted to address imbalanced data. Their strategy yielded an accuracy rate of 70% and underscored the effectiveness of ensemble approaches in classifying diabetic retinopathy (DR).

3. PROPOSED WORK

3.1Convolutional Neural Network

In a traditional feed-forward convolutional neural network (CNN), the initial convolutional layer, which receives the input, is the sole layer that directly connects to the output of the preceding convolutional layer. This layer generates an output feature map, which is then transmitted to the subsequent convolutional layer. Consequently, each layer has "L" direct connections to the next layer. However, as CNNs deepen or expand in levels, they encounter the challenge of the "vanishing gradient" problem. This issue implies that as the network's depth increases, some information may diminish or become lost, diminishing the network's learning capacity.

DenseNets address this problem by modifying the conventional CNN architecture and enhancing connectivity between layers. The term "Densely Connected Convolutional Network" denotes an architecture in which every layer is interconnected with all others. Consequently, there exist L(L+1)/2 direct links between "L" layers.

The proposed model is based on the DenseNet121 architecture, which accepts an RGB image of 224 × 224 pixels. The model's weights were pre-trained using the ImageNet dataset, leveraging the learned features to optimize the fully connected layer's output weights adequately. The feature extraction process occurs within the convolutional layers, while the final layer handles classification. A softmax activation function is applied to the model's output to assign probabilities to each class. Notably, each output from a convolutional layer is concatenated with subsequent layers within the same block, as depicted in Figure 2, showcasing a distinctive characteristic of DenseNet.

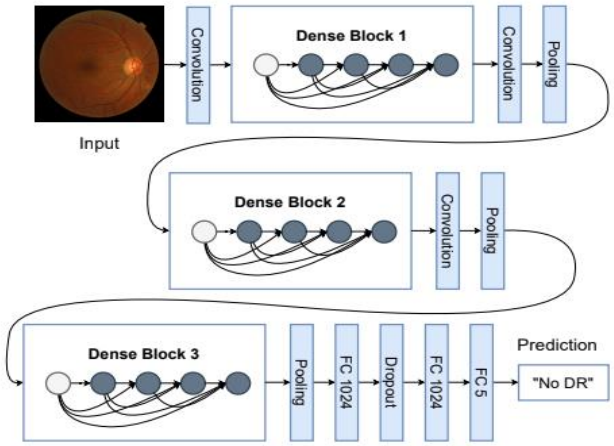

Fig-2: DenseNet-121 Architecture

The features extracted from the image after processing through the convolutional layers are subsequently fed into the classification stage. The classifier comprises two fully connected layers. Following a dropout layer with a dropout probability of 50%, the first layer of the system consists of 1024 units with a ReLU activation function. The final layer comprises 5 units, representing the classes, and utilizes a softmax activation function.

3.2 Retina image Dataset

In this study, the dataset is sourced from Kaggle and is known as the APTOS dataset. It comprises 3662 labeled images for training and 1928 unlabeled images for testing purposes. The dataset can be accessed via the Kaggle Dataset Download link: https://www.kaggle.com/c/aptos2019-blindness-detection/data. Originally published as a

competition on the Kaggle platform, the APTOS dataset consists of fundus oculi images captured under various conditions and of different sizes. Sample images are provided below as shown in Figure 3.

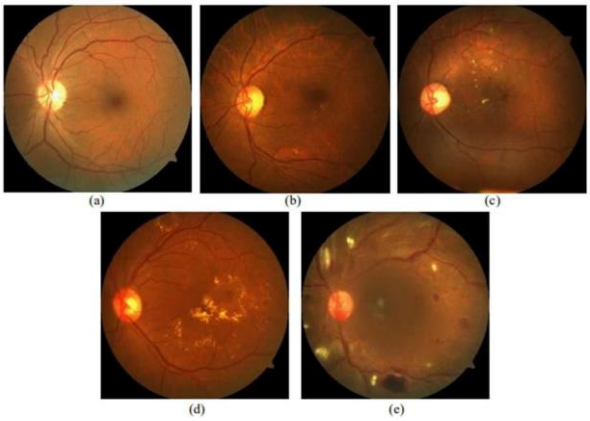

Fig-3: Images in the Dataset

4. METHODOLOGY

4.1 Data-Preprocessing

As part of the preprocessing step, all images in the datasets underwent center cropping, resulting in only the retina's fundus being retained, as it is the most critical part of the image for our task. Additionally, the images were resized to dimensions of 224 x 224 pixels as in Figure 4. This standardization ensures consistency in image sizes and focuses the model's attention on the relevant features of the retinal images.

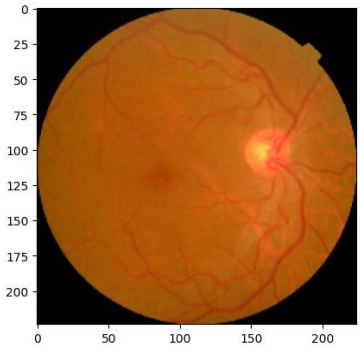

Fig-4: Preprocessed image

4.2 Data Augmentation

Data augmentation involves generating new data samples from existing training data through various transformations such as cropping, padding, flipping, rotating, and resizing. This technique is commonly used to increase the diversity and quantity of training data, which in turn enhances the performance of machine learning models. By exposing the model to a wider range of variations in the input data, data augmentation helps prevent overfitting and improves the generalization ability of the model.

4.3 Model Implementation

The CNN model employed in this study is built upon the DenseNet121 architecture, renowned for its dense connectivity patterns. Leveraging pre-training on the ImageNet dataset, DenseNet121 serves as the feature extraction backbone, capturing rich visual features from retinal fundus images via transfer learning. To tailor the model for diabetic retinopathy classification, additional layers are added to the DenseNet121 base. A global average pooling layer reduces spatial dimensions, followed by a dense layer with ReLU activation to capture high-level representations. Dropout regularization is incorporated to mitigate overfitting by randomly deactivating neurons during training.

The output layer consists of a dense layer with softmax activation, producing a probability distribution over five classes of retinal diseases. The model is compiled using SGD optimizer with momentum, categorical cross-entropy loss, and accuracy metric. Data augmentation techniques are employed to enhance performance and combat overfitting. Augmented images, generated using ImageDataGenerator, undergo random transformations like rotation and flipping, enriching the training dataset for better generalization.

Hyperparameter tuning is conducted using the Keras Tuner library, optimizing dropout rate and learning rate. The hyperband optimization algorithm efficiently explores parameter space, identifying the configuration maximizing validation accuracy. During training, callbacks such as reduce learning rate and early stopping monitor performance and prevent overfitting. The model is trained on augmented data and evaluated on a validation set to assess loss and accuracy, ensuring robust performance in classifying diabetic retinopathy.

4.4 Result Analysis

The trial consisted of training the model over 9 epochs while monitoring its performance. At the end of this trial, the validation accuracy reached approximately 76.45%. However, it's worth noting that the highest validation accuracy achieved during training was approximately 78.67%, indicating a positive trend of improvement over the training period.

Optimal hyperparameters were identified to maximize validation accuracy, including a learning rate of 0.001 and a dropout rate of 0.5. These parameters significantly influenced the model's performance, showcasing their importance in training CNNs effectively.

Throughout the training process, the model showed consistent improvement, as seen in the steady increase in

accuracy and decrease in loss. By the 9th epoch, the model achieved an impressive accuracy of 84.29%, demonstrating its ability to learn and recognize patterns within the dataset effectively.

Dynamic adjustments to the learning rate were implemented during training, with a reduction to 0.0001 after the 8th epoch. This adaptive learning rate strategy likely contributed to the model's enhanced performance, allowing for fine-tuning of parameters and convergence towards optimal solutions.

After training, evaluation on the validation set revealed promising results, with a validation loss of 0.5139 and a validation accuracy of 80.38% as shown in Chart -2 & 1 respectively. These metrics highlight the model's effectiveness in accurately classifying diabetic retinopathy, suggesting its potential application in clinical settings for disease diagnosis and management as shown in chart 3.

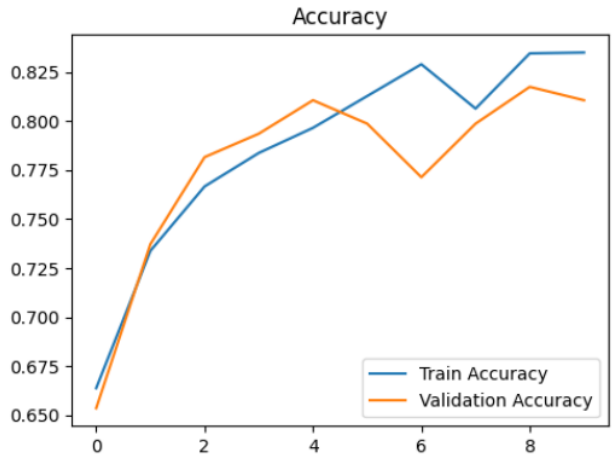

Chart -1: Model Accuracy

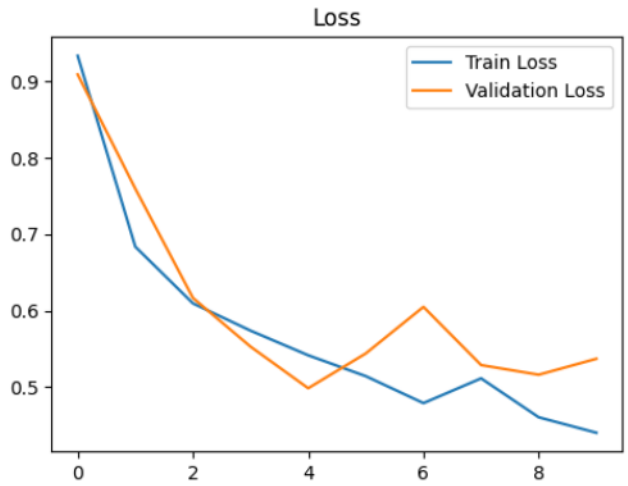

Chart -2: Model Loss

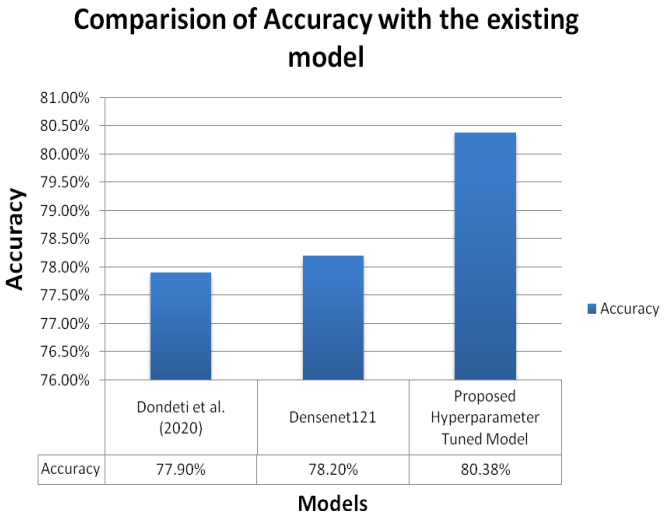

Chart -3: Comparison of Accuracy with the existing System

5. CONCLUSION

In conclusion, the trained convolutional neural network (CNN) model has demonstrated promising performance in effectively classifying diabetic retinopathy using retinal fundus images. Through meticulous training and hyperparameter optimization, the model has achieved noteworthy results. Its capability to accurately classify diabetic retinopathy, along with its robustness in learning and identifying patterns within the dataset, highlights its potential applicability in clinical settings.

As a valuable tool for disease diagnosis and management, the CNN model holds promise in assisting healthcare professionals in early detection and intervention for diabetic retinopathy, ultimately leading to improved patient outcomes and enhanced quality of care. However, further research and validation on larger datasets and real-world clinical scenarios are essential to ascertain the model's efficacy and generalizability, ensuring its reliability and effectiveness in practical healthcare settings.

6. FUTURE WORK

Future research directions aim to enhance the diabetic retinopathy classification model's efficacy and broaden its applicability in clinical practice. Firstly, the creation of a benchmark dataset will establish a standard for evaluating model performance, enabling fair comparisons across different studies. Secondly, exploring alternative preprocessing functions and architectures, including multilabel approaches, holds promise for improving the model's accuracy and robustness. Thirdly, investigating a bounding box detection approach could provide valuable insights into the localization and extent of abnormalities in retinal images, facilitating more precise diagnosis and treatment planning. These proposed avenues for future work

seek to advance the state-of-the-art in diabetic retinopathy classification, ultimately benefiting patients and healthcare professionals alike.

REFERENCES

[1] Mellitus, D. Diagnosis and classification of diabetes mellitus. Diabetes Care 2005, 28, S5–S10.

[2] Cree, M.J.; Olson, J.A.; McHardy, K.C.; Sharp, P.F.; Forrester, J.V. A fully automated comparative microaneurysm digital detection system. Eye 1997, 11, 622–628.

[3] Yun, W.L.; Rajendra Acharya, U.; Venkatesh, Y.; Chee, C.; Min, L.C.; Ng, E. Identification of different stages of diabetic retinopathy using retinal optical images. Inf. Sci. 2008, 178, 106–121.

[4] Gargeya, R.; Leng, T. Automated identification of diabetic retinopathy using deep learning. Ophthalmology 2017, 124, 962–969.

[5] Chetoui, M.; Akhloufi, M.A. Explainable Diabetic Retinopathy using EfficientNET. Proceedings of the 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montréal, QC, Canada, 20–24 July 2020

[6] Dondeti, V.; Bodapati, J.D.; Shareef, S.N.; Veeranjaneyulu, N. Deep Convolution Features in Non-linear Embedding Space for Fundus Image Classification. Rev. d'Intell. Artif. 2020, 34, 307–313.

[7] Qummar, S.; Khan, F.G.; Shah, S.; Khan, A.; Shamshirband, S.; Rehman, Z.U.; Khan, I.A.; Jadoon, W. A deep learning ensemble approach for diabetic retinopathy detection. IEEE Access 2019, 7, 150530–150539.

[8] American Diabetes Association. Diagnosis and classification of diabetes mellitus. Diabetes Care, 28(Suppl. 1), S5–S10. doi:10.2337/diacare.28.suppl_1.S5.

[9] [2] Cree, M.J., Olson, J.A., McHardy, K.C., Sharp, P.F., & Forrester, J.V. (1997). A fully automated comparative microaneurysm digital detection system. Eye, 11(5), 622–628. doi:10.1038/eye.1997.160.

[10] [3] Yun, W.L., Rajendra Acharya, U., Venkatesh, Y., Chee, C., Min, L.C., & Ng, E. (2008). Identification of different stages of diabetic retinopathy using retinal optical images. Information Sciences, 178(1), 106–121. doi:10.1016/j.ins.2007.07.012.

[11] [4] Gargeya, R., & Leng, T. (2017). Automated identification of diabetic retinopathy using deep learning. Ophthalmology, 124(7), 962–969. doi:10.1016/j.ophtha.2017.02.008.

[12] [5] Ting, D.S.W., Cheung, C.Y.-L., Lim, G., Tan, G.S.W., Quang, N.D., Gan, A., ... & Wong, T.Y. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA, 318(22), 2211–2223. doi:10.1001/jama.2017.18152.

[13] [6] Gulshan, V., Peng, L., Coram, M., Stumpe, M.C., Wu, D., Narayanaswamy, A., ... & Webster, D.R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402–2410. doi:10.1001/jama.2016.17216.

[14] [7] Abràmoff, M.D., Lou, Y., Erginay, A., Clarida, W., Amelon, R., Folk, J.C., & Niemeijer, M. (2016). Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Investigative Ophthalmology & Visual Science, 57(13), 5200–5206. doi:10.1167/iovs.16-19964.

[15] [8] Ting, D.S.W., Cheung, G.C.M., Wong, T.Y. (2019). Diabetic retinopathy: global prevalence, major risk factors, screening practices and public health challenges: a review. Clinical & Experimental Ophthalmology, 47(4), 536–547. doi:10.1111/ceo.13396.

[16] 9] Sahlsten, J., Jaskari, J., Kivinen, J., Turunen, L., Jaanio, E., & Pietilä, J. (2020). Deep learning fundus image analysis for diabetic retinopathy and macular edema grading. Scientific Reports, 10(1), 1-10. doi:10.1038/s41598-020-61905-7.

[17] [10] Natarajan, S., Jain, A., Krishnan, R., Rogye, A., Sivaprasad, S., & Rao, C. K. (2020). Evaluating performance of deep learning algorithms for diabetic retinopathy detection. Computers in Biology and Medicine, 122, 103801. doi:10.1016/j.compbiomed.2020.103801.

[18] [11] Costa, P., Galdran, A., Meyer, M. I., Abràmoff, M. D., Niemeijer, M., & Mendonça, A. M. (2017). Towards adversarial retinal image synthesis. In International Workshop on Simulation and Synthesis in Medical Imaging (pp. 42-51). Springer, Cham. doi:10.1007/978-3-319-67561-9_5.

[19] [12] An, T., Doan, T., Cao, Q., & Jain, A. K. (2019). Adversarial representation learning for diabetic retinopathy analysis. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 0-0). doi:10.1109/CVPRW.2019.00169.