Volume 9, Issue 7, July – 2024 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUL605

OctoVision: A Smart System for Diabetic Retinopathy Disease Detection

[1]Govind Haldankar (Professor)
Electronics Engineering Department
Sardar Patel Institute of Technology
Mumbai, India

[2]Gaurav Galbal
Electronics Engineering Department
Sardar Patel Institute of Technology
Mumbai, India

[3]Vikram Choudhary
Electronics Engineering Department
Sardar Patel Institute of Technology
Mumbai, India

[4]Sanket Kanoja
Electronics Engineering Department
Sardar Patel Institute of Technology
Mumbai, India

Abstract:- Diabetic retinopathy (DR) is the major cause of vision impairment and blindness in diabetics. Early detection and treatments are critical in preventing irreparable retinal damage. Manual detection of diabetic retinopathy by an ophthalmologist takes a long time, and patients must suffer greatly during this time. This paper presents an automated approach for rapid DR detection using the DenseNet-121 architecture. Our model achieves an accuracy exceeding 80%, with a precision score of 81% and a recall score of 86%, indicating its high effectiveness in detecting DR. Additionally, we developed a server-based implementation where the trained model is deployed. Images captured by a camera are uploaded to a cloud server, which processes them and sends back a diagnostic response. This study contributes to continuing efforts to create efficient and reliable techniques for early DR identification, resulting in earliermanagement and better patient outcomes.

Keywords:- *Diabetic Retinopathy, DenseNet Architecture, Retinal Fundus Images, Cloud Server, Real-time Screening.*

I. INTRODUCTION

Diabetic Retinopathy (DR) is a significant consequence of diabetes mellitus that causes damage to the retinal blood vessels as a result of persistently high blood glucose levels. In severe circumstances, DR can result in considerable vision loss and perhaps complete blindness. Early signs of DR include black spots, floaters, blurred vision, and difficulties differentiating colours. Early and correct identification of DR is critical for avoiding irreparable blindness.

Globally, approximately one-third of the estimated 285 million individuals with diabetes exhibit symptoms of DR. The overall number of cases of DR is expected to increase from 126.6 million in 2010 to 191.0 million by 2030. In the early stage of diabetes, known as Non-Proliferative Diabetic Retinopathy (NPDR), little red spots (microaneurysms) form on the retina, which might indicative of hemorrhages. Blood vessel damage can produce exudates, which include fluid and fatty deposits, to flow into the retina.

As DR advances, abnormal blood vessel development (proliferative diabetic retinopathy) can occur, causing retinal scarring or bleeding and eventually leading to progressive vision loss and blindness. DR accounts for 2.6% of global blindness cases. Major risk factors for developing DR include the duration of diabetes, high levels of hemoglobin A1c, and hypertension. Regular screening is crucial for diabetic patients to ensure that DR is detected at an early stage. DR detection traditionally involves a physician's examination of retinal imaging for the shape and appearance of different types of lesions. Available physical tests to detect diabetic retinopathy includes pupil dilation, visual acuity test, optical coherence tomography, etc. But they are time consuming and patients need to suffer a lot. This paper focuses on detection of diabetic retinopathy using deep learning techniques. Our trained model may be used to diagnose, process, and post camera photos in real-time on a cloud server, providing a useful and effective way to check for DR early on.

II. LITERATURE REVIEW

In the first study conducted in 2019 to classify diabetic retinopathy using the aptos dataset, which involved a rigor-ous investigation. Models such as inceptionv3, vgg16, and resnet50 were meticulously evaluated. The findings revealed that inceptionv3, with its exceptional accuracy of 96.18%, outperformed other models. Nevertheless, the study stressed the importance of conducting additional research to evaluate the model's effectiveness across various demographic groups and external datasets to ensure its applicability in different contexts. Furthermore, improving interpretability by utilizing explainable AI techniques and mitigating the model's vulner- ability to misclassifications are vital for ensuring transparency in medical decision-making. To fully harness the potential of artificial intelligence in preventive and personalized medicine for

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUL605

identifying diabetic retinopathy, future research shouldfocus on enhancing the model to align with real-world challenges.

In a study conducted in 2023 at the Sindh Institute of Ophthalmology Visual Sciences, researchers employed fundus images to detect diabetic retinopathy using a modified convolutional neural network (cnn). The real-time testing incorporated an image quality rating evaluated by clinical experts. This research highlighted the importance of having a large dataset with labeled examples and introduced the area under the receiver operating characteristic curve (auc) as a comprehensive metric for evaluating performance. Using ultra-wide-field fundus pictures and deep learning, the 2021 project aimed to detect diabetic retinopathy early. In order to eliminate unwanted elements, the suggested approach au- tomatically subdivided the ETDRS 7 Standard Fields (7SF). The ResNet-34 model, with the aid of optic disc and macula recognition for precise picture alignment, identified diabetic retinopathy using Ultra-Wide-Field (UWF) fundus images. For efficient diabetic retinopathy identification, the pre-trained ResNet-34 model showed strong performance in combining UWF fundus pictures with the ETDRS 7SF, even with a very small dataset.[2]

In 2020, machine learning made it easier to detect diabetic retinopathy by extracting yellow exudates from RGB photos through preprocessing. The abnormality segmentation process combined Random Forest, K-Nearest Neighbours, and Sup- port Vector Machines into a hybrid classification technique. This approach improved the accuracy of identifying retinal abnormalities greatly, demonstrating its potential to advance ophthalmological diagnosis.[3]

The 2019 study investigated the identification and catego- rization of diabetic retinopathy using adaptive boosting and colour space conversion and vessel removal to improve the quality of retinal images by resolving problems with illumi- nation and contrast. Promising F1 Score values, sensitivity, accuracy, and precision were displayed by the Adaptive Boost- ing Algorithm. With regard to diabetic retinopathy, the ANN approach—specifically, Architecture III—rose to prominence for its exceptional precision and accuracy.[4]

III. DATASET & METHODS

The dataset used in this research comes from Kaggle, a reliable website well-known for its wide range of competitions and dataset collections. This particular dataset consists of 3,380 images that have been assigned to training and 376 images that have been assigned to testing. The training dataset was further split into training and validation subsets, keeping an 80:20 ratio in each case, to ensure robust model evaluation. A variety of data augmentation methods were used on the photos to improve the dataset and strengthen the resilience of the model. These methods mitigated the effects of any unclear images and simulated real-world fluctuations through random flips, rotations, zooms, and brightness modifications.

The identification of diabetic retinopathy within the dataset is based on an analysis of various visual characteristics, in- cluding the appearance, number, spread, and size of exudates, microaneurysms, and hemorrhages. Exudates, characterized by bright yellowish areas, are distinguished from the optic disc by their color variance. The presence of lipids within rup- tured blood vessels contributes to the formation of exudates. Similarly, the rupture of microaneurysms within blood vessels results in the formation of hemorrhages.

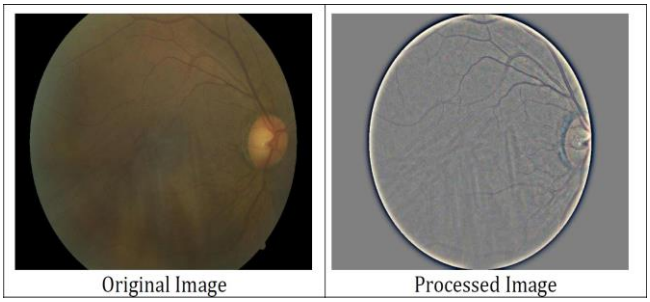

Fig 1 Image with no DR

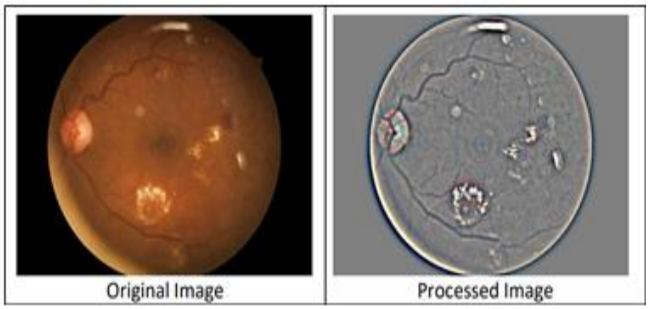

Fig 2 Image with DR

IV. IMAGE PREPROCESSING

The preprocessing of images is a critical phase in enhancing the quality and relevance of input data before integration into the deep learning model. The primary objective is to improve the model's capacity to extract meaningful features and make precise predictions.

To optimize the interpretability of captured images, a strate- gic combination of advanced techniques was employed. First, a circle mask was carefully placed to every picture, keeping the centre area and removing unnecessary parts from the edges. The goal of this exact process was to draw attention to and preserve the key elements of the photograph.

Moreover, a sophisticated enhancement process was imple- mented, involving the judicious amalgamation of the original image with a Gaussian-blurred counterpart. This method was carefully calibrated to emphasize intrinsic features while con- currently mitigating noise. The incorporation of the Gaussian- blur variant introduced a controlled smoothing effect, con- tributing to a more refined and visually comprehensible rep- resentation.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUL605

V. METHODOLOGY

The DenseNet-121 model is used as the backbone archi- tecture in the suggested methodology because of its high efficiency in feature extraction and classification tasks, making it ideal for image-based applications. DenseNet-121's unique structural qualities allow for the continuous flow of informa- tion across layers, encouraging feature reuse and addressing issues such as vanishing gradients. Transition blocks in the architecture control spatial dimensions and channel depth, whilst bottleneck layers improve computational efficiency. The network comprises an initial convolution layer, followed by multiple dense blocks interspersed with transition layers.

These dense blocks are designed to concatenate outputs from preceding layers, thereby improving gradient flow and feature propagation.

The DenseNet-121 model architecture has many key com- ponents, including an initial convolution layer, batch normal- ization, and ReLU activation. This is followed by a maximum pooling layer. The model then moves through a succession of dense blocks, each containing multiple convolutional layers, with transition layers in between to reduce spatial dimensions and prevent overfitting. The bottleneck layers within these blocks use 1x1 and 3x3 convolutions to enhance computational efficiency. Following the final dense block, global average pooling is used to build a fixed-size feature vector, which is then passed through a fully connected layer with softmax activation to get a probability distribution over the target classes.

The DenseNet-121 model was built with the Keras package, which includes pre-trained models for transfer learning. The model was built using the Adamax optimizer and a categorical cross-entropy loss function. To improve performance and avoid overfitting, data augmentation and actions such as learningrate reduction, early stopping, and model checkpointing were used during training. The model's final output is a probability distribution between two classes, with the highest probability indicating the anticipated class. Class 0 denotes the normal class, whereas Class 1 represents the abnormal class. This architectural choice, as well as the subsequent output inter- pretation, contribute to the proposed method's resilience and utility for detecting diabetic retinopathy.

VI. CLOUD DEPLOYMENT AND REAL-TIME IMAGE PROCESSING

The DenseNet-121 model, after being trained and validated, is deployed on a cloud server to leverage the computational power and scalability of cloud infrastructure. The system will be able to process several requests at once and provide prompt, accurate replies thanks to this configuration. The photos go through the previously mentioned preparation pipeline as soon as they are received by the cloud server. This includes applying a circular mask to focus on the relevant parts of the image and using Gaussian blurring to enhance key features. The preprocessed images are then fed into the deployed DenseNet-121 model.

The model processes the images and generates predictions in real-time. The output, which includes a probability distri- bution across the predefined classes (normal and abnormal), is then sent back to the user's device.

VII. RESULTS AND DISCUSSION

Our developed model demonstrated a commendable ac- curacy of around 80%, indicating its capability to correctly predict outcomes across the dataset. This level of accuracy is promising for the intended application of diabetic retinopathy detection.

The precision measure reflects how many of the positively detected occurrences were truly right. It is calculated as the ratio of true positives to the total of true positives and false positives. The precision for Class 0 (no diabetic retinopathy) is 0.74, meaning that 74% of the instances predicted as no diabetic retinopathy were indeed true negatives. For Class 1 (diabetic retinopathy), the precision is 0.81, highlighting the model's efficiancy in correctly identifying positive cases. Thus, 81% of the instances predicted as diabetic retinopathy were accurate, indicating a high level of precision for identifying this condition.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUL605

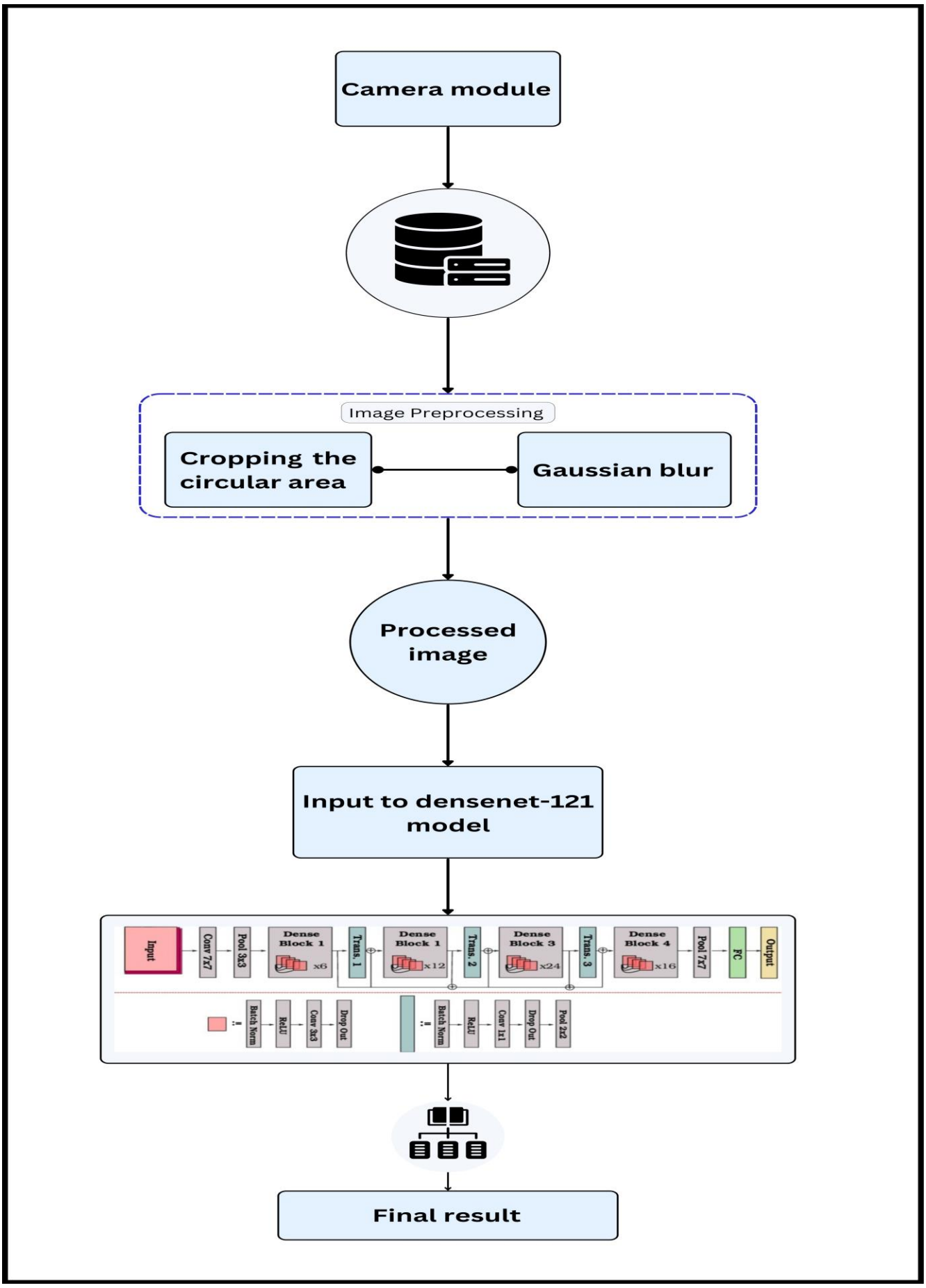

Fig 3 Flowchart

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUL605

Recall, which reflects the model's ability to identify all ac- tual positive instances, is another critical metric. It is calculated as the ratio of true positives to the sum of true positives and false negatives. The recall for Class 0 is 0.86, indicating that the model successfully identified 86% of the actual instances of no diabetic retinopathy. Conversely, the recall for Class 1 is 0.66, meaning that the model correctly identified 66% ofthe actual instances of diabetic retinopathy.

VIII. CONCLUSION

The use of DenseNet-121 architecture in this work is a big step forward in applying deep learning to healthcare, particularly diabetic retinopathy detection. When combined with a unique weighted Gaussian blur preprocessing approach, DenseNet-121 improves our capacity to distinguish subtle aspects of diabetic retinopathy from retinal pictures.

Furthermore, the use of a cloud server architecture for real-time image processing and model inference demonstrates our approach's scalability and usability. By installing the model on a cloud server, we offer seamless picture capture via networked cameras, allowing for quick diagnosis and action.The insights derived from this research expand our un- derstanding of diabetic retinopathy and provide robust models and interpretability analyses. These outcomes establish a solid foundation for future advancements in automated screening for diabetic retinopathy, with the overarching goal of improving patient outcomes and alleviating healthcare burdens.

Early detection and diagnosis enabled by our methodology are critical in mitigating the risk of blindness and addressing the severe implications of diabetic retinopathy. This study emphasizes the social impact of advancements in automated screening processes, advocating for enhanced patient care and making a significant contribution to continuing efforts to successfully treat diabetic retinopathy.

REFERENCES

[1]. K. NEM, M. Loey, M. H. N. Taha, and H. N. E. T. Mohamed, "Deep transfer learning models for medical diabetic retinopathy de- tection," *Acta Inform. Med.*, vol. 27, no. 5, pp. 327-332, 2019, doi: 10.5455/aim.2019.27.327-332.

[2]. A. Bajwa, N. Nosheen, K. I. Talpur, and S. Akram, "A prospective study on diabetic retinopathy detection based on modify convolutional neural network using fundus images at Sindh Institute of Ophthalmology and Visual Sciences," *Diagnostics*, vol. 13, no. 3, p. 393, 2023, doi: 10.3390/diagnostics 13030393.

[3]. R. Revathy, B. S. Nithya, J. J. Reshma, S. S. Ragendhu, and M. D. Sumithra, "Diabetic retinopathy detection using machine learning," *Int. J. Eng. Res. Technol.*, vol. 9, 2020.

[4]. A. Dhakal, L. P. Bastola, and S. Shakya, "Detection and classification of diabetic retinopathy using adaptive boosting and artificial neural network," *Int. J. Adv. Res. Publ.*, vol. 3, no. 8, pp. 191-196, 2019. [Online]. Available: http://www.ijarp.org/online-papers-publishing/aug2019.html

[5]. F. Alzami, A. Arya Megantara, and A. Z. Fanani, "Diabetic retinopathy grade classification based on fractal analysis and random forest," in *Int. Seminar on Appl. for Tech. of Info. and Comm.*, 2019.

[6]. S. Choudhury, S. Bandyopadhyay, S. K. Latib, D. K. Kole, and C. Giri, "Fuzzy C means based feature extraction and classification of diabetic retinopathy using support vector machines," in *Int. Conf. Commun. SignalProcess.*, 2016.

[7]. S. Sangwan, V. Sharma, and M. Kakkar, "Identification of different stages of diabetic retinopathy," in *Int. Conf. Comput. Comput. Sci.*, 2015.

[8]. V. Gulshan et al., "Development and validation of a deep learning algo- rithm for detection of diabetic retinopathy in retinal fundus photographs," *JAMA*, vol. 316, no. 22, p. 2402, 2016.

[9]. R. Gargeya and T. Leng, "Automated identification of diabetic retinopathy using deep learning," *Ophthalmology*, vol. 124, no. 7, pp. 962-969, 2017.

[10]. K. Oh, H. M. Kang, D. Leem, H. Lee, K. Y. Seo, and S. Yoon, "Early detection of diabetic retinopathy based on deep learning and ultra-wide- field fundus images," *Nature Sci. Rep.*, vol. 11, no. 1897, 2021. [Online].

[11]. A. Sharma, S. Shinde, I. I. Shaikh, M. Vyas, and S. Rani, "Machine learning approach for detection of diabetic retinopathy with improved pre- processing," in *Int. Conf. Comput., Commun., and Intell. Syst. (ICCCIS)*, 2021. [Online].

[12]. A. Dhakal, L. P. Bastola, and S. Shakya, "Detection and classification of diabetic retinopathy using adaptive boosting and artificial neural network," *Int. J. Adv. Res. Publ.*, 2019.

[13]. Kaggle, "Diabetic Retinopathy Detection Dataset." [Online]. Available: https://www.kaggle.com/ competitions/diabetic-retinopathy-detection/data

[14]. K. Shinde and S. Kulkarni, "Business oriented enhancement model for diabetic retinopathy detection," in *Int. Conf. Business Manage., Innov., and Sustain. (ICBMIS)*, 2020.

[15]. V. Sapra et al., "Diabetic retinopathy detection using deep learning with optimized feature selection," *Traitement du Signal*, vol. 41, no. 2, pp. 781-790, 2024, doi: 10.18280/ts.410219.

[16]. N. M. Al-Moosawi and R. S. Khudeyer, "ResNet-n/DR: Automated di- agnosis of diabetic retinopathy using a residual neural network," *Telkom- nika*, vol. 21, no. 5, pp. 1051-1059, 2023, doi: 10.12928/ TELKOM-NIKA.v21i5.24515.

[17]. Z. Gao et al., "Diagnosis of diabetic retinopathy using deep neuralnetworks," *IEEE Access*, vol. 7, pp. 3360-3370, 2019, doi: 10.1109/AC- CESS.2018. 2888639.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUL605

[18]. Y. S. Kanungo, B. Srinivasan, and S. Choudhary, ”Detecting diabetic retinopathy using deep learning,” in *IEEE Int. Conf. Recent Trends in Electron., Info. and Commun. Technol. (RTEICT)*, 2017, pp. 801-804,doi: 10.1109/RTEICT.2017.8256708.

[19]. A. Sebastian, O. Elharrouss, S. Al-Maadeed, and N. Almaadeed, ”A survey on deep-learning-based diabetic retinopathy classification,” *Diag- nostics*, vol. 13, no. 3, p. 345, 2023, doi: 10.3390/ diagnostics13030345.

[20]. K. Bhatia, S. Arora, and R. Tomar, ”Diagnosis of diabetic retinopa- thy using machine learning classification algorithm,” in *IEEE Int. Conf. Next Gen. Comput. Technol. (NGCT)*, 2016, pp. 347-351, doi:10.1109/NGCT.2016.7877439.

[21]. K. Bhatia, S. Arora, and R. Tomar, ”Diagnosis of diabetic retinopa- thy using machine learning classification algorithm,” in *IEEE Int. Conf. Next Gen. Comput. Technol. (NGCT)*, 2016, pp. 347-351, doi:10.1109/NGCT.2016.7877439.