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Region-Based Convolutional Neural Networks Based Automated Detection and Classification of Diabetic Retinopathy

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Abstract - One of the main causes of vision impairment in diabetic patients is diabetic retinopathy (DR), which is brought on by long-term elevated blood sugar levels damaging the retinal blood vessels. Early and accurate detection is essential for effective treatment. Deep learning-based approaches have shown significant promise in automated Diabetic Retinopathy (DR) diagnosis by leveraging advanced feature extraction and classification techniques. This study explores a deep learning framework utilizing a Region-based Convolutional Neural Network (RCNN) for Diabetic Retinopathy (DR) detection and severity classification. Region-based Convolutional Neural Network (RCNN) is employed for robust feature extraction, effectively capturing complex patterns and localized lesions in retinal images. The proposed model processes retinal fundus images to detect abnormalities with high precision and classify Diabetic Retinopathy (DR) into different severity levels. The results indicate that the Region-based Convolutional Neural Network (RCNN) based approach enhances classification performance, providing a reliable and scalable solution for automated Diabetic Retinopathy (DR) screening.

Key Words**:** Diabetic Retinopathy, Region-based Convolutional Neural Network, Random Forest, Data Sets, Performance Metrics.

1.Introduction

Diabetes can induce diabetic retinopathy, a dangerous eye condition that can result in blindness if not detected early. Timely diagnosis and treatment is crucial for preventing blindness. However, doctors' manual detection can be laborious and prone to mistakes made by humans. To solve this problem, this study focuses on using a computer-based method called Region-Based Convolutional Neural Networks (R-CNNs) to automatically detect and classify diabetic retinopathy from eye images. This approach aims to make the diagnosis faster, more accurate, and more reliable, helping doctors provide better care for patients. The Fig 1 shows the Comparison Between normal Retina and Diabetic Retina

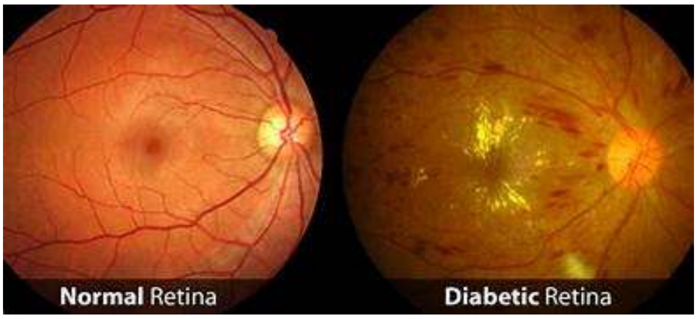

Fig -1: Comparison Between normal Retina and Diabetic Retina

Diabetic retinopathy progresses through five distinct stages represented in Fig 2, beginning with a normal retina that shows no signs of damage. Early clinical signs in the moderate non-proliferative stage are microaneurysms, which are tiny bulges in the retina's blood vessels. When it progresses to the level of moderate non-proliferation, the damage becomes more pronounced with increased microaneurysms, hemorrhages, and the beginning of blood vessel blockage, which can lead to leakage and mild vision impairment. The blood supply to the retina is greatly reduced in the severe non-proliferative stage due to the blockage of several retinal blood vessels. Cotton wool patches, "assuaging" of vessels, and large hemorrhages are characteristics of this stage. Proliferative diabetic retinopathy is the last and most severe stage, in which oxygen deprivation causes the retina to begin producing new, aberrant blood vessels. These veins are delicate and prone to bleeding, which can cause scarring, separation from the retina, and, in lack of therapy, blindness or significant vision impairment.

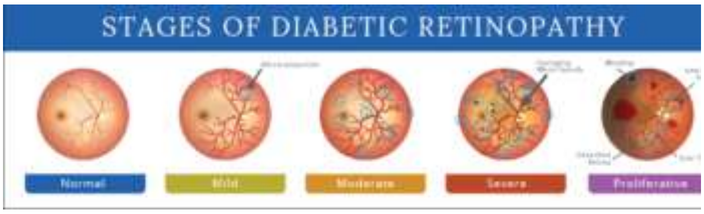

Fig -2: Different Stages of Diabetic Retinopathy

A ResNet18-based Deep Convolutional Neural Network (DCNN) integrated with a novel Region Scoring Map (RSM) to identify discriminative regions in retinal images. Trained on a dataset of 30,000 images and tested on 5,000, the model achieved accuracy. However, its performance was hindered by difficulties in detecting microaneurysms due to down sampling and by dataset class imbalance [1]. A hybrid method combining Histogram of Oriented Gradients (HOG), Sharlet Transform, and Region-Based Convolutional Neural Networks (RCNN) features within a Faster Region-Based Convolutional Neural Networks (R-CNN) framework. This model was trained on huge fundus images collected from three public datasets and achieved significant improvements in detection accuracy, sensitivity, and specificity. Despite its effectiveness, the approach faced challenges such as variations in brightness and colour among images from different fundus cameras, and the need for larger datasets to enhance generalization and support real-time clinical applications [2]. A DenseNet-65-based Faster Region-Based Convolutional Neural Networks (R-CNN) model aimed at classifying Diabetic retinopathy (DR) into five severity levels. DenseNet-65 served as the backbone for feature extraction, while Faster Region-Based Convolutional Neural Networks (R-CNN) performed lesion detection. The model, evaluated on the Kaggle dataset comprising images, outperformed other architectures like ResNet and EfficientNet-B5. Nonetheless, it encountered issues such as false positives and limited dataset diversity, emphasizing the need for further validation across varied datasets and improvement in real-time processing [3]. Presented a Region-Based Convolutional Neural Networks (R-CNN) based model that applied image preprocessing techniques such as green channel extraction, adaptive histogram equalization, and optic disc removal. The model employed region proposals and a 10-layer CNN classifier, achieving accuracy on the IDRiD dataset. However, the study was constrained by limited computational resources, which led to slower training times, and the small dataset size, which affected model generalization [4]. Discussed an enhanced Faster Region-Based Convolutional Neural Networks (R-CNN) model incorporating GLCM-based feature extraction along with adaptive histogram equalization and contrast enhancement. Trained on a combination of Kaggle and APTOS datasets (huge number of images), the model achieved a high accuracy outperforming previous architectures like VGG-19 and ResNet. Nevertheless, the model exhibited high computational demands, and despite strong performance, still produced some false positives and negatives, indicating a need for manual verification and further real-world testing [5].

2. Literature Review

The literature highlights the growing role of advanced deep learning and machine learning models in the automated detection and classification of diabetic retinopathy (DR). Region-based Convolutional Neural Networks (RCNNs), including variants such as Faster R-CNN and Mask R-CNN, have demonstrated significant improvements in lesion detection and DR severity grading due to their strong localization and feature extraction capabilities. Studies employing ResNet, Dense Net, and Inception-ResNet-v2 as backbone architectures integrated with RCNNs have achieved high accuracy, though challenges such as small lesion detection, dataset imbalance, and computational resource demands persist. Enhancements such as ROI Align, Feature Pyramid Networks (FPN), and the incorporation of handcrafted features like Histogram of Oriented Gradients (HOG) and GLCM have further strengthened performance but also added to model complexity. Complementary methods like Random Forests have also been explored for classification and feature selection, particularly when fused with clinical data or used as an auxiliary classifier. Despite the progress, many models face limitations including false positives, limited generalization across datasets, and sensitivity to image quality and lighting conditions. The collective research underlines the necessity for robust preprocessing, large and diverse datasets, and optimized network architectures to achieve reliable and scalable DR detection solutions.

In paper [6], authors adapted Mask R-CNN with ResNet-50/101 backbones and data augmentation for nucleus segmentation, achieving IoU. However, small dataset size and high computational cost affected performance.

In this paper [7], authors explained the classification of diabetes using CNN method through alerts.

In article [8], authors developed a machine learning based diabetes classification system for remote area patients also.

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In research paper [9], authors developed a Faster R-CNN model with Inception-ResNet-v2 for feature extraction and Random Forest for classification, reaching accuracy. Misclassifications and high resource requirements were issues.

In research paper [10], authors explained Detectron2 with Faster R-CNN and Mask R-CNN (R50-FPN), achieving accuracy. Dataset size and small lesion detection were limitations.

In article [11], researchers developed an IoT based health monitoring system for diabetic patients using different sensors and measured different health parameters.

In paper [12], authors used Random Forest and logistic regression on fundus and systemic data for DR classification. The approach suffered from potential misclassification due to reliance on pre-graded fundus images.

In paper [13], authors compared nine classifiers including Random Forest for DR screening, finding no clear best performer. Although it needed a lot of computing, the Gaussian Process received the highest score.

In article [14], authors applied Random Forest, SVM, and KNN for feature selection and classification, noting RF-based techniques improved accuracy, but data imbalance and lack of deep learning limited results.

In research paper [15], authors explained a Random Forest Fuzzy Entropy (RFFE) model for diabetes classification with accuracy. Overfitting and limited dataset diversity were major challenges.

In paper [16], authors built a Decision Support System using Random Forest and logistic regression, achieving strong early-stage DR detection. Variability in lighting reduced accuracy in advanced DR.

In article [17], authors used OCT imaging and a Deep Fusion Classification Network for DR detection, finding good results but noting limited dataset size and noisy images as issues.

In research paper [18], authors HOG features with SVM and Random Forest for NPDR classification, achieving accuracy. Classification varied across DR stages, requiring larger datasets.

In paper [19], authors applied Random Forest to predict DR based on systemic factors, achieving accuracy for DR and STDR. Lack of image-based input limited precision.

In article [20], authors developed an IoT based health monitoring system for remote area patients to measure their health parameters and communicated to doctor as well as to the patient also.

3. Existing Method

The Random Forest algorithm for the detection and classification of diabetic retinopathy. Multiple decision trees are constructed using the Random Forest ensemble learning technique, which then combines the results to increase prediction accuracy and reduce overfitting. It analyses features extracted from retinal images, such as texture and colour, to identify signs of diabetic retinopathy. This method is effective and relatively easy to implement, making it a commonly used approach in earlier stages of automated eye disease detection. Fig 3 displays the RF figure.

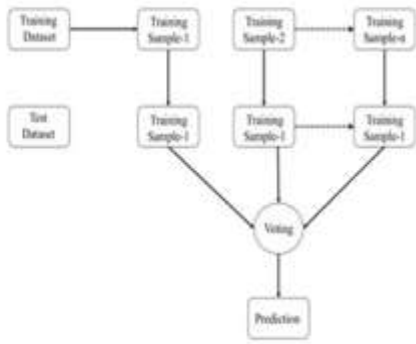

Fig -3: Block Diagram of Existing Method

Training Dataset: This block represents the labelled images or data used to train the model. Retinal fundus photos annotated with different levels of DR severity (e.g., No DR, Mild, Moderate, Severe, Proliferative) are included in the instance of DR.

Training Sample-1, Sample-2, ..., Sample-n: These are random subsets (samples with replacement) taken from the training dataset. Each subset is used to train a separate base classifier (e.g., decision trees in the Random Forest). In DR detection, each classifier learns different patterns, such as the presence of microaneurysms, hemorrhages, exudates, etc.

Test Dataset: This block contains unseen retinal images used to evaluate the trained ensemble model. These images do not have labels during inference and are used to test the model's generalization and prediction capability.

Voting: Each trained model makes a prediction (e.g., classifies the image as No DR, Mild DR, etc.). A voting mechanism (usually majority voting for classification tasks) is used to aggregate predictions from all the models. This helps reduce overfitting and increases robustness by combining different perspectives.

Prediction: The final output is the aggregated class label for the test sample, derived from the ensemble's consensus. In DR, this could be the predicted stage of diabetic retinopathy for a given retinal image.

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4. Region-based Convolutional Neural Network (RCNN)

RCNN (Region-based Convolutional Neural Network) is employed to detect and classify diabetic retinopathy lesions from retinal fundus images, shown in Fig 4. The process begins with the input of high-resolution retinal images, where RCNN uses a region proposal method, such as Selective Search, to identify candidate areas that may contain lesions. These region proposals are then passed through a convolutional neural network (CNN) for deep feature extraction, capturing critical visual patterns such as texture, shape, and intensity variations. Each region is subsequently classified using a trained classifier to determine whether it contains a diabetic retinopathy lesion (such as microaneurysms or hemorrhages) and to assign a severity grade. The anticipated lesion locations are further refined in parallel by a bounding box regression phase. The final output includes lesion classifications with bounding boxes overlaid on the original image, aiding in precise and automated grading of diabetic retinopathy.

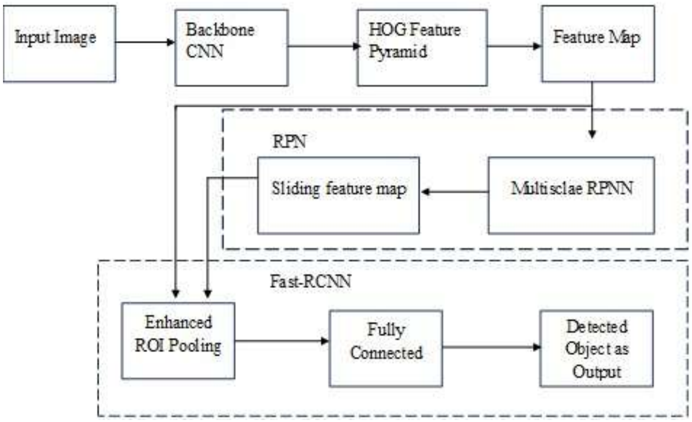

Fig -4: Block Diagram of R-CNN

Input Image: The process starts with inputting a retinal fundus image, which may contain lesions like microaneurysms, hemorrhages, or exudates.

Backbone CNN: A Convolutional Neural Network (CNN), such as ResNet or VGG, extracts deep features from the image. These features help identify patterns and structures that are not visible to the naked eye but crucial for DR diagnosis.

HOG Feature Pyramid: Histogram of Oriented Gradients (HOG) is used to capture gradient and texture information at multiple scales, enhancing lesion detection—especially important for detecting small objects like microaneurysms.

Feature Map: The combined output of CNN and HOG pyramid results in a feature map, which highlights potential regions of interest by representing visual features such as edges, textures, and intensity.

Sliding Feature Map: A sliding window moves across the feature map to These regions are possible locations for lesions or abnormalities in the retina.

Multiscale RPNN: A Multiscale Region Proposal Neural Network (RPNN) generates bounding boxes of varying sizes for detecting lesions at different scales. This is crucial in DR, where lesions range in size and shape.

Enhanced ROI Pooling: For accurate sorting, the offered regions are aligned into predefined sizes using Region of Interest (ROI) pooling. The "enhanced" version improves spatial alignment, helping in more precise localization of lesions.

Fully Connected Layer: These layers classify the pooled regions as specific DR lesion types (e.g., hemorrhages, exudate) and refine the bounding boxes for more accurate detection.

Detected Object as Output: A collection of identified lesions with class names and bounding boxes is the end result, which enables medical professionals or automated systems to evaluate the existence and seriousness of the lesions. of diabetic retinopathy.

5. Results and Discussions

The dataset used for diabetic retinopathy classification shows a clear imbalance, with the “Healthy” class dominating both the training and testing sets, followed by a fair representation of Mild, Severe, and Proliferative DR cases, while Moderate DR is severely underrepresented in Fig 5.

Fig - 5: Class Distribution in Train and Test Datasets

Sample image visualizations in Fig 6 confirm the dataset’s diversity in retinal pathology presentation, which is crucial for robust model training.

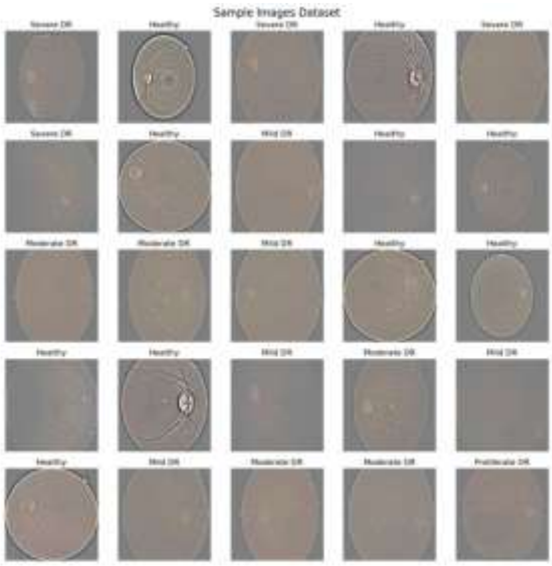

Fig - 6: Sample Images Datasets

In Fig 7 Comparative performance analysis between the Random Forest (RF) and Region-based Convolutional Neural Network (R-CNN) models reveals that R-CNN outperforms RF across all metrics accuracy, precision, recall, and F1-score indicating the superior capability of deep learning-based approaches in handling complex image features and subtle DR indicators.

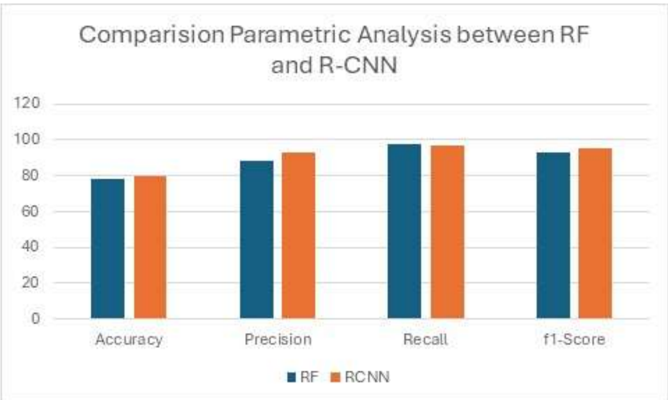

Fig - 7: Comparison Parametric Analysis between RF and R-CNN

In Fig 8 the example of a correctly labelled Mild DR image further supports the model's practical classification effectiveness, especially in identifying early-stage symptoms.

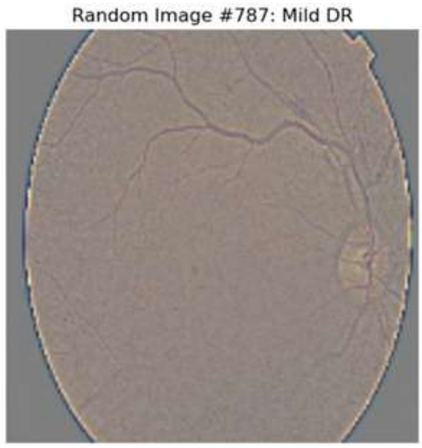

Fig - 8: Output of RCNN Method

CONCLUSIONS

The work demonstrates the effectiveness of deep learning models, particularly R-CNN, in accurately classifying different stages of diabetic retinopathy, outperforming traditional models like Random Forest across all performance metrics. Despite the dataset imbalance, the model shows strong potential in detecting both early and advanced stages of DR, as evidenced by the sample visual results and metric comparisons. Future improvements can focus on balancing the dataset and adopting more advanced architectures. Additionally, deploying the model in real-time diagnostic tools could enhance accessibility in remote areas.

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REFERENCES

01. Farnaaz, N., & Jabbar, M. A. (2016). Random Forest Modeling for Network Intrusion Detection System. Procedia Computer Science, 89, 213-217. Elsevier. DOI: 10.1016/j.procs.2016.06.047.

02. R. Casanova, S. Saldana, E. Y. Chew, R. P. Danis, C. M. Greven, and W. T. Ambrosius, "Application of Random Forests Methods to Diabetic Retinopathy Classification Analyses," PLoS ONE, vol. 9, no. 6, pp. 1-8, June 2014. DOI: 10.1371/journal.pone.0098587.

03. S. Mohammadian, A. Karsaz, and Y. M. Roshan, "A Comparative Analysis of Classification Algorithms in

Diabetic Retinopathy Screening," in Proceedings of the 7th International Conference on Computer and Knowledge Engineering (ICCKE 2017), October 26-27, 2017, Ferdowsi University of Mashhad, pp. 84-89. DOI: Not available.

04. R.-C. Chen, C. Dewi, S.-W. Huang, and R. E. Caraka, "Selecting Critical Features for Data Classification Based on Machine Learning Methods," Journal of Big Data, vol. 7, no. 52, pp. 1-26, 2020. DOI: 10.1186/s40537-020-00327-4

05. A. U. Ruby, G. C. Chandran, S. J. TJ, C. BN, and R. Patil, "RFFE – Random Forest Fuzzy Entropy for the Classification of Diabetes Mellitus," AIMS Public Health, vol. 10, no. 2, pp. 422–442, May 2023. DOI: 10.3934/publichealth.2023030.

06. K. Akyol, Ş. Bayir, and B. Şen, "A Decision Support System for Early-Stage Diabetic Retinopathy Lesions," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 8, no. 12, pp. 369-379, 2017.

07. MahaLakshmi B, Dr. G. SrinivasaRao, Bhavya Sree Ch, Lakshmi Durga P, Naga Niharika P, Chaitanya Lakshmi A," IoT Based System for Classification of Diabetes Using Convolutional Neural Network Algorithm", International Journal of Scientific Development and Research (IJSDR), Volume 8 Issue 4, ISSN: 2455-2631 April 2023, PP 1285-1290. 08. MahaLakshmi.B, Srinivasa Rao.G, Tejaswi, Supraja.K, Ramya.A, Sumythri.V," Machine Learning- based Diabetes Classification using Raspberry-Pi", International Journal for MultidisciplinaryResearch (IJFMR)- Volume 5, Issue 2, E-ISSN: 2582-2160 March-April 2023, PP1-6

09. Venkatesh, R., Gandhi, P., Choudhary, A., Kathare, R., Chhablani, J., Prabhu, V., Bavaskar, S., Hande, P., Shetty, R., Reddy, N. G., & Yadav, N. K. (2024). Evaluation of Systemic Risk Factors in Patients with Diabetes Mellitus for Detecting Diabetic Retinopathy with Random Forest Classification Model. Diagnostics, 14(1765), 1-10. DOI: 10.3390/diagnostics14161765.

10. MahaLakshmi B, Lavanya M, Rajeswari Haripriya G, Sushmasri K, Teja M, Jayasri M" Design and Implementation of IoT Based Smart Health Monitoring System for Diabetic Patients Using Wireless Sensor Networks", International Journal of Information Technology (IJIT) – Volume 8 Issue 3, ISSN: 2454-5414, May – Jun 2022, PP16-19.

11. Pan, J., Yong, Z., Sui, D., & Qin, H. (2018). Diabetic Retinopathy Detection Based on Deep Convolutional Neural Networks for Localization of Discriminative Regions. Proceedings of the 2018 International Conference on Virtual Reality and Visualization (ICVRV),46-52 IEEE. DOI: 10.1109/ICVRV.2018.00016.

12. Diabetic Retinopathy Detection Method Using Fused Features from Retina Images. IEEE Access, 11, 124331-124349. https://doi.org/10.1109/ACCESS.2023.3330104.

13. Albahli, S., Nazir, T., Irtaza, A., & Javed, A. (2021). Recognition and Detection of Diabetic Retinopathy Using Densenet-65 Based Faster-RCNN. Computers, Materials & Continua, 67(2), 1333-1351. https://doi.org/10.32604/cmc.2021.014691.

14. Athira, T. R., Sivadas, A., George, A., Paul, A., & Gopan, N. R. (2019). Automatic Detection of Diabetic Retinopathy using R-CNN. International Research Journal of Engineering and Technology (IRJET), 6(5), 5595-5600.

15. Sri Sravya, V., Srinivasu, P. N., Shafi, J., Hołubowski, W., & Zielonka, A. (2024). Advanced Diabetic Retinopathy Detection with the R–CNN: A Unified Visual Health Solution. International Journal of Applied Mathematics and Computer Science, 34(4), 661–678. https://doi.org/10.61822/amcs-2024-0044

16. Johnson, J. W. (2018). Adapting Mask-RCNN for Automatic Nucleus Segmentation. arXiv preprint, arXiv:1805.00500.

17. Bai, T., Pang, Y., Wang, J., Han, K., Luo, J., Wang, H., Lin, J., Wu, J., & Zhang, H. (2020). An Optimized Faster R-CNN Method Based on DRNet and RoI Align for Building Detection in Remote Sensing Images. Remote Sensing, 12(5), 1-16, 762. https://doi.org/10.3390/rs12050762

18. Wang, J., Luo, J., Liu, B., Feng, R., Lu, L., & Zou, H. (2020). Automated diabetic retinopathy grading and lesion detection based on the modified R-FCN object-detection algorithm. IET Computer Vision, 14(1), 1-8. https://doi.org/10.1049/iet-cvi.2018.5508

19. Jung, Y., & Kim, D. (2022). Feature Extraction of Non-proliferative Diabetic Retinopathy Using Faster R-CNN and Automatic Severity Classification System Using Random Forest Method. Journal of Information Processing Systems, 18(5), 599-613. https://doi.org/10.3745/JIPS.04.0252

20. MahaLakshmi Bollimuntha, Kalpana Murugan," Design and Implementation of an Interoperable IoT Based Health Monitoring System for Diabetes, IEEE 5TH international conference at ICSSIT-2023, January 2023, Francis Xavier Engineering College, Tirunelveli, India

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