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Vision Saver: ML - Based Early Detection of Diabetic Retinopathy

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ABSTRACT: Diabetic Retinopathy (DR) is a progressive eye disease that can lead to vision impairment and blindness if not detected early. With the employment of Convolutional Neural Networks (CNN), Vision Saver classifies retinal images into different levels of DR. The model is trained on varying severity levels of DR from one publicly available dataset using transfer learning techniques for better accuracy. An adjustment-oriented pipeline of preprocessing includes image augmentation, resize, and contrast enhancement for efficient feature extraction. The model is implemented using PyTorch allowing efficient training and scalability. Very high precision and recall results have been observed in the classification model making it a good candidate for DR early screening. ResNet, a deep residual learning framework, was utilized to improve feature extraction by addressing vanishing gradient issues, enabling more accurate classification of DR stages. Vision Saver's performance was reviewed against the following metrics: accuracy, F1-score which are useful in distinguishing between the DR phases. It could lessen the manual diagnosis by providing the opportunity for ophthalmologists to diagnose early-stage DR and reduce complications. This development would help the disabled vision agents in performing the effective diagnosis and early intervention on the diabetic cases having better lost vision and quality of life.

KEYWORDS: Diabetic Retinopathy (DR), Convolutional Neural Networks, Transfer Learning, PyTorch, ResNet, Early Diagnosis, Machine learning in Healthcare, Image Classification, Vision Saver.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a progressive eye disorder that affects people with diabetes, leading to vision impairment and, in severe cases, blindness. The World Health Organization (WHO) reports that over 320 million individuals worldwide suffer from DR, positioning it as one of the leading preventable causes of blindness, especially in working-age populations. The condition advances through different stages, ranging from non-proliferative DR (NPDR) to advanced proliferative DR (PDR), underscoring the importance of early identification for effective treatment. Traditional diagnosis of DR relies on the manual examination of retinal fundus images by ophthalmologists, a process that can be time-consuming, subjective, and limited by healthcare resources, particularly in isolated or underserved areas. The manual grading technique is also prone to variability, complicating large-scale screening efforts. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable effectiveness in medical image assessment by adeptly capturing hierarchical spatial features. Deep learning frameworks such as ResNet-152 have greatly advanced Diabetic Retinopathy detection by mitigating vanishing gradient problems and enhancing feature extraction capabilities. [1]

The application of Torch and Torchvision in model creation offers a versatile framework for training CNN-based models effectively, ensuring precise classification of Diabetic Retinopathy severity levels. Moreover, Pillow is essential in image preprocessing, covering tasks like resizing, enhancing contrast, and reducing noise, which boosts model precision. The combination of transfer learning with pre-trained models improves adaptability across varied datasets, enhancing the robustness of the system for real-world use. AI-enabled Diabetic Retinopathy detection reduces the occurrence of false positives and false negatives and facilitates easy integration into electronic health records (EHRs), aiding ophthalmologists in Artificial Intelligence supported decision-making. In addition, scalable deployment methods, including cloud-based platforms and mobile health applications, broaden the availability of Diabetic Retinopathy screenings to distant and under-resourced regions. Although there are challenges concerning model interpretability and acceptance in clinical settings, machine learning-enhanced Diabetic Retinopathy detection holds the promise to revolutionize early diagnosis and treatment results, considerably alleviating the global impact of diabetic eye disease.

A. Objective

The main goal of this project is to create Vision Saver, a machine learning-driven system for the early identification of Diabetic Retinopathy using retinal fundus images. By utilizing Convolutional Neural Networks (CNNs) and ResNet-152 architectures, the model intends to accurately categorize images into various DR severity levels, aiding ophthalmologists in prompt diagnosis and treatment planning. Torch and Torch vision offer a solid framework for model creation and training, facilitating efficient handling of large-scale image datasets. [2] Furthermore, Pillow is essential in image preprocessing, executing vital tasks such as resizing, contrast enhancement, and noise reduction, all of which boost model accuracy. To improve predictive performance, Vision Saver includes transfer learning by employing pre-trained weights from extensive medical imaging datasets, enhancing generalization across a variety of retinal image datasets. The system is designed to reduce false positives and false negatives, thus enhancing the dependability of DR detection.

B. Significance and impact

Diabetic Retinopathy (DR), a serious eye disease impacting eyesight, can result from long-term diabetes. Globally, the impact of DR affects approximately 463 million people. In 2019, DR accounted for 22. 27% of blindness cases. In India, a survey from 2015 to 2019 indicated that 16. 9% of the population—approximately 72. 96 million individuals—are impacted by DR. Furthermore, a Times of India article, published November 14, 2021, projected 77 million DR cases within India. The increasing occurrence of diabetes and diabetic retinopathy emphasizes the critical requirement for early identification and treatment to avoid permanent vision impairment. Employing machine learning (ML)-based screening instruments can boost access to prompt diagnosis, lessen the workload on ophthalmologists and better overall patient results. [3]

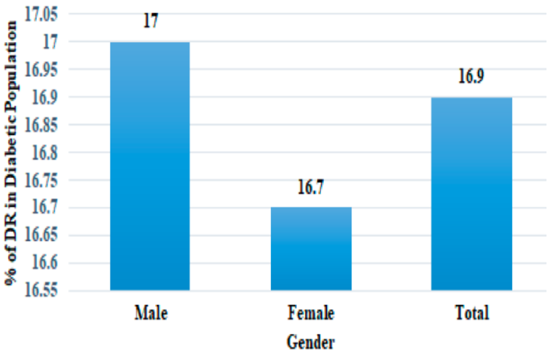

Fig.1. Gender-wise prevalence of DR

II. LITERATURE REVIEW

Diabetic Retinopathy (DR) is a significant factor contributing to vision loss in diabetic patients, and prompt detection is vital for successful treatment. Conventional diagnostic techniques depend on the manual review of retinal fundus images by ophthalmologists, which is both time-consuming and subjective, as well as resource-intensive. To address these drawbacks, machine learning (ML) has been investigated as a more effective and automated solution for DR identification. Initial ML-based research utilized traditional models, including Support Vector Machines (SVM) and Random Forest (RF), to categorize retinal images based on features extracted manually (Quellec et al., 2017). Although these techniques yielded some enhancements in detection precision, they faced challenges in recognizing intricate patterns in retinal images and often necessitated substantial preprocessing. The advent of deep learning, especially Convolutional Neural Networks (CNNs), greatly improved DR detection by facilitating automatic feature extraction from retinal images (Gulshan et al.,2016).

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CNNs have shown outstanding effectiveness in detecting early-stage DR indicators such as microaneurysms and hemorrhages, rendering them more dependable for large-scale screenings. Additional advancements were made by utilizing transfer learning, where pretrained CNN models such as VGG16, ResNet, and InceptionNet were optimized on DR datasets like Messidor and EyePACS (Apostolopoulos et al.,2020). More contemporary studies have investigated hybrid models, combining CNNs with Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to observe temporal trends in DR development (Lam et al.,2018).[4] These methodologies have improved diagnostic precision and reliability. However, obstacles such as model interpretability, dataset imbalance, and practical clinical implementation continue to be areas of ongoing research. Explainable AI (XAI) strategies, including Grad-CAM and SHAP, are being explored to enhance model clarity and aid ophthalmologists in their decision-making processes (Doshi et al., 2020). The future of ML-driven DR detection involves blending AI-powered models with telemedicine technologies to enhance accessibility and early diagnosis, particularly in resource-constrained environments.

III. METHODOLOGY

The approach taken in this study employs a structured method for gathering, processing, and evaluating retinal fundus images through the use of machine learning (ML) models for automatic detection of Diabetic Retinopathy (DR). The aim is to create an effective and precise system that can recognize various stages of DR. The methodology includes the following significant steps:

1. Data Collection

Effective DR detection necessitates high-quality retinal images sourced from dependable origins. In this study, data is collected from:

- Publicly Available Datasets – Extensive, annotated DR datasets like Messidor, EyePACS, Kaggle DR, and APTOS 2019 provide high-resolution fundus images classified according to DR severity.
- Hospital and Clinical Records – Retinal images from diabetic patients acquired through collaborations with healthcare facilities. These datasets feature patient metadata such as age, duration of diabetes, and previous DR diagnosis.

The dataset comprises images categorized across five severity levels: No DR (0), Mild DR (1), Moderate DR (2), Severe DR (3), and Proliferative DR (4).

2. Data Preprocessing

Since the raw retinal images may exhibit noise, variations in illumination, and inconsistencies, preprocessing is crucial for enhancing model accuracy.

i. Image Enhancement and Augmentation

Image enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) are utilized to improve contrast, whereas Gaussian filtering serves to reduce noise. To make input dimensions consistent, images are resized to 224×224 pixels, aligning with ResNet-152's specifications. Pixel normalization is also applied, scaling values between 0 and 1. In addition, data augmentation methods, such as rotation, flipping, zooming, and brightness adjustment, are utilized via Torchvision transforms to improve model generalization and avoid overfitting. For creating the model, the system employs Convolutional Neural Networks (CNNs), using ResNet-152 specifically, a deep learning architecture renowned for its excellent image classification capabilities. A pre-trained ResNet-152 model is fine-tuned for DR detection, modifying its fully connected layers to accommodate five-class classification.

3. Model development

The system employs Convolutional Neural Networks (CNNs), specifically ResNet-152, for efficient Diabetic Retinopathy (DR) classification. The deep learning architecture is designed to leverage the power of pre-trained ResNet-152, which is fine-tuned for DR detection by modifying its fully connected layers to accommodate a five-class classification system. A softmax activation function is employed in the final layer to generate a probability distribution across the DR severity levels, ensuring accurate classification. For implementation, Torch and Torchvision are utilized to build and train the deep learning model, providing essential functionalities for efficient processing and optimization. Furthermore, the Pillow (PIL) library is incorporated into the system for image loading and manipulation, enabling straightforward preprocessing of retinal fundus images prior to their input into the CNN model. These tools function

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collaboratively to guarantee effective model learning of retinal image patterns, thus facilitating precise early detection of DR.

4. Model training and optimization

Model training and optimization are crucial steps in developing an accurate and efficient Diabetic Retinopathy (DR) detection system using machine learning. The goal is to train a deep learning model capable of effectively classifying retinal fundus images into various DR severity levels while minimizing errors. This procedure entails defining the architecture, loss function, optimization algorithm.[3]

i. Model Architecture

In this study, Convolutional Neural Network (CNNs) and ResNet-152, are used due to their strong ability to extract hierarchical spatial features from retinal images. ResNet-152 utilizes skip connections, enabling deeper architectures without the vanishing gradient problem. The architecture consists of convolutional layers, batch normalization, ReLU

$$\text{Softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

activation, and fully connected layers, ending with a softmax layer to classify images into five DR severity levels:
where z_i is the output of the last layer for class i, and N is the total number of classes (five in this case).

ii. Loss Function

To measure classification error, Categorical Cross-Entropy Loss is used. This function calculates the difference between the true class label y and the predicted probability y^:
where $\mathbf{y_i}$ is 1 for the correct class and 0 otherwise. The model aims to minimize this loss during training.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

5. Model Evaluation

After training, the model is evaluated using key performance metrics such as Accuracy, Precision and F1-Score.

i . Accuracy

Accuracy measures the overall correctness of the model. TP, TN, FP, and FN refer to True Positive, True Negative, False Positive, False Negative respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

ii. Precision

Precision (Positive Predictive Value - PPV) measures how many of the predicted positive cases are actually positive. It indicates the reliability of positive predictions and is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

A high precision means that when the model predicts a positive case (e.g., DR present), it is likely to be correct.

6. Model Deployment

Once the model attains an acceptable level of performance, it is implemented for practical applications to enable the early detection of Diabetic Retinopathy. The trained model is initially exported using frameworks such as TorchScript for PyTorch models to ensure greater compatibility across various platforms. Deployment may be executed on cloud platforms including AWS, Google Cloud, or Azure, guaranteeing scalability and accessibility, or on edge devices like mobile applications and embedded systems for immediate DR detection. Furthermore, a web or mobile interface is created to permit healthcare professionals to upload retinal images and obtain automated predictions, thereby rendering the system user-friendly and practical for clinical applications.[4]

IV. EXISTING SOLUTION

Existing solutions for the detection of Diabetic Retinopathy (DR) predominantly depend on manual diagnoses conducted by ophthalmologists, which tends to be time-consuming, subjective, and significantly reliant on the availability of experts. Traditional machine learning methods, including Support Vector Machines (SVM) and Decision Trees, have been employed for the classification of DR; however, these methods necessitate extensive feature engineering and are restricted in their capacity to manage complex retinal images.[5] In recent years, deep learning models, specifically Convolutional Neural Networks (CNNs), have markedly enhanced the accuracy of DR detection by autonomously learning hierarchical features from retinal fundus images. Various CNN-based architectures, including VGG16, InceptionNet, and MobileNet, have been utilized for the screening of DR, yet they encounter challenges such as overfitting and obstacles in training deep networks. To address these constraints, residual learning-based architectures, such as ResNet, have been introduced, facilitating the training of deeper networks without a decline in performance [5].

V. PROPOSED SOLUTION

The Vision Saver system has been developed to identify Diabetic Retinopathy (DR) utilizing Convolutional Neural Networks (CNNs) and ResNet architectures.

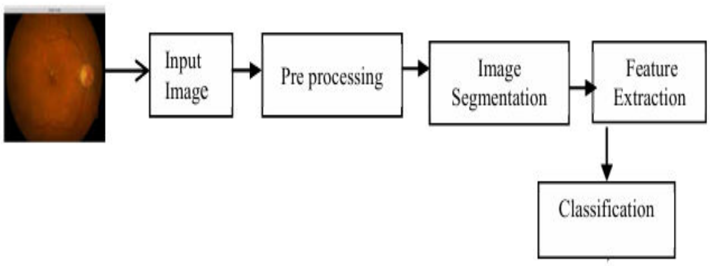

Fig.2. DR Process Flow

Through the integration of CNN for the extraction of features and ResNet for advanced learning and improved gradient flow, the proposed system augments the accuracy and dependability of DR detection. The system adheres to a systematic procedure to categorize retinal fundus images into various levels of DR severity with efficiency.

i. Input Image

In the Vision Saver project, retinal fundus images utilized for the detection of Diabetic Retinopathy (DR) are sourced from publicly accessible Kaggle datasets, including the APTOS 2019 Blindness Detection and Diabetic Retinopathy Detection datasets. These datasets comprise thousands of labelled retinal images acquired using fundus cameras, representing various levels of DR severity. The images have been resized to 1024x1024 and cropped to eliminate much of the black space. [6]

ii. Pre - processing

Raw retinal images often contain noise, inconsistent illumination, and differing contrast levels. To enhance model performance, pre-processing techniques, including grayscale conversion, contrast enhancement, Gaussian filtering, and data augmentation (rotation, flipping, and brightness adjustments), are employed. This phase ensures that the CNN model receives high-quality images for feature extraction.

iii. Image Segmentation

Image segmentation is an essential phase in the detection of Diabetic Retinopathy (DR), as it facilitates the identification of critical retinal structures such as blood vessels, microaneurysms, hemorrhages, and exudates, which are crucial indicators of DR severity [7]. By utilizing CNN and ResNet-based segmentation techniques, the Vision Saver system improves the accuracy of DR detection. CNNs contribute to spatial feature learning, whereas ResNet enhances deep feature extraction and training stability, culminating in more precise, automated DR screening that assists ophthalmologists in early diagnosis and treatment planning.

iv. Feature Extraction

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CNNs are employed to automatically extract significant hierarchical features from retinal images. The convolutional layers identify key patterns such as microaneurysms, hemorrhages, and exudates, which are vital for determining DR severity. The pooling layers decrease dimensionality while preserving essential features, enabling the model to concentrate on pertinent aspects of the image. [8]

v. Deep Feature Learning with ResNet

Standard CNN architectures face challenges like vanishing gradients when training deep networks. To overcome this, ResNet (Residual Network) is incorporated into the system. ResNet introduces skip connections (residual connections) that allow gradients to flow efficiently through the network, enabling deeper models to learn complex patterns without performance degradation [9]. By using ResNet the system can extract richer and more detailed features, improving classification accuracy.

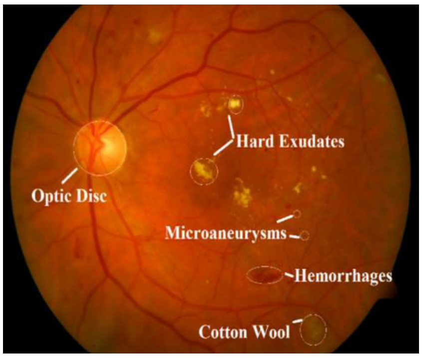

Fig.3. Diabetic retinopathy retinal image

vi. Classification of Diabetic Retinopathy (DR) Levels

Diabetic Retinopathy (DR) is classified into five severity levels based on the presence and extent of retinal abnormalities such as microaneurysms, hemorrhages, exudates, and neovascularization. The Vision Saver system uses CNN and ResNet-based deep learning models to automatically classify retinal fundus images into these DR severity levels.[10]

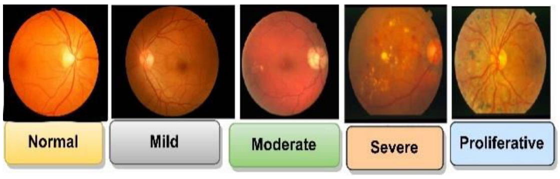

Fig.4. Diabetic retinopathy Classification

- **No DR (Normal Stage - Grade 0):** The retina appears healthy with no signs of abnormalities. There is no presence of microaneurysms, hemorrhages, or exudates. Patients at this stage do not require immediate treatment but need regular screening.
- **Mild Non-Proliferative DR (NPDR - Grade 1):** This is the earliest stage of DR, characterized by the presence of a few microaneurysms, which are small bulges in blood vessels. There is no major damage to retinal blood vessels, and usually, no noticeable vision impairment occurs at this stage.
- **Moderate Non-Proliferative DR (NPDR - Grade 2):** At this stage, there is an increased number of microaneurysms and small hemorrhages in the retina. Partial blockage of blood vessels leads to mild leakage of fluids and proteins. Early signs of retinal swelling (edema) may begin to affect vision.
- **Severe Non-Proliferative DR (NPDR - Grade 3):** This stage is marked by a more extensive blockage of retinal blood vessels, reducing oxygen supply. There is a significant increase in hemorrhages, exudates, and cotton wool spots, which indicate damaged nerve fibers. The risk of progressing to proliferative DR is high, requiring close monitoring and potential medical intervention.

- **Proliferative DR (PDR - Grade 4):** This is the most advanced stage, where new, abnormal blood vessels (neovascularization) begin to grow. There is a high risk of vitreous hemorrhage, retinal detachment, and permanent vision loss. Immediate treatment, such as laser therapy or surgery, is required to prevent blindness.[11]

VI. FUTURE SCOPE

The future scope of this research focuses on improving DR detection through advanced machine learning models and multi-modal data integration, including patient history and lab results. Enhancing deep learning architectures, such as vision transformers and hybrid models, can further improve accuracy and generalizability. Deploying the model on cloud platforms or mobile applications will enable real-time DR detection, making it accessible in remote areas. Additionally, increasing model interpretability through explainable AI will build trust among healthcare professionals. Continuous training with diverse datasets will enhance robustness and reduce biases. Integrating the system with telemedicine can facilitate early diagnosis and treatment, while collaborations with medical institutions and health programs can promote large-scale adoption, ultimately reducing preventable blindness worldwide.[12]

VII. CONCLUSION

The Vision Saver system employs CNN and ResNet for the automated and early detection of diabetic retinopathy (DR) utilizing retinal fundus images. By incorporating image preprocessing, segmentation, and classification based on deep learning, it effectively identifies retinal abnormalities including microaneurysms, hemorrhages, and exudates, categorizing DR into various severity levels. This methodology enhances the efficiency of screening, minimizes diagnostic delays, and aids ophthalmologists in facilitating timely interventions, ultimately averting vision loss in patients with diabetes. With its scalable and cost-effective characteristics, Vision Saver possesses the potential to transform the diagnosis of retinal diseases and telemedicine applications on a global scale. By facilitating real-time DR detection and ensuring accessibility in remote regions, it significantly contributes to comprehensive screening programs. Partnerships with healthcare organizations and governmental initiatives can further broaden its scope, establishing it as a crucial instrument in the reduction of blindness associated with DR worldwide.[13]

REFERENCES

[1] Teo, Z.L.; Tham, Y.C.; Yu, M.; Chee, M.L.; Rim, T.H.; Cheung, N.; Bikbov, M.M.; Wang, Y.X.; Tang, Y.; Lu, Y.; et al. Global prevalence of diabetic retinopathy and projection of burden through 2045: Systematic review and meta-analysis. Ophthalmology 2021, 1281580–1591.

[2] Vashist, P.; Senjam, S.S.; Gupta, V.; Manna, S.; Gupta, N.; Shamanna, B.R.; Bhardwaj, A.; Kumar, A.; Gupta, P. Prevalence of diabetic retinopathy in India: Results from the National Survey 2015–19. Indian J Ophthalmol. 2021, 69, 3087. [Google Scholar] [CrossRef] [PubMed]

[3] Kaur J. Mitta D. A generalized method for the detection of vascular structure in pathologicalretinal images. Biocybernetics and Biomedical Engineering, Volume 37, Issue 1, 2017, Pages 184-200.

[4] SohiniRoychowdhury, Dara D Koozekanani, Keshab K Parhi, "DREAM: Diabetic retinopathy analysis using Machine learning", IEEE J Biomed Health Inform. 2014 Sep;18(5) pg:1717-28. doi: 10.1109/JBHI.2013.2294635.

[5] Koetting, C. The Four Stages of Diabetic Retinopathy; Modern Optometry: Fairfax, VA, USA, 2019; pp. 21–24. [Google Scholar]

[6] Farrikh Alzami, Abdussalam, Rama Arya Megantara and Ahmad Zainul Fanani, "Diabetic Retinopathy Grade Classification based on Fractal Analysis and Random Forest", International Seminar on Application for Technology of Information and Communication, 2019.

[7] Shinde, R.; Patil, S.; Kotecha, K.; Ruikar, K. Blockchain for securing ai applications and open innovations. J. Open Innov. Technol. Mark. Complex. 2021, 7, 189. [Google Scholar]

[8] Zhang, X.; Thibault, G.; Decencière, E.; Marcotegui, B.; Laè, B.; Danno, R.; Cazuguel, G.; Quellec, G.; Lamard, M.; Massin, P.; et al. Exudate detection in colour retinal images for mass screening of diabetic retinopathy.

[9] Perdomo, O.; Otalora, S. Rodríguez, F.; Arevalo, J.; González, F.A. A novel machine learning model based on exudate localization to detect diabetic macular edema. In Proceedings of the Ophthalmic Medical Image Analysis Third International Workshop, Athens, Greece, 21 October 2016.

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[10] Sopharak, A.; Uyyanonvara, B.; Barman, S. Automatic exudate detection from non-dilated diabetic retinopathy retinal images using fuzzy c-means clustering. Sensors 2009, 9, 2148–2161. [Google Scholar] [CrossRef] [PubMed]

[11] Huang, C.; Zong, Y.; Ding, Y.; Luo, X.; Clawson, K.; Peng, Y. A new deep learning approach for the retinal hard exudates detection based on super-pixel multi-feature extraction and patch-based CNN. Neurocomputing 2021, 452, 521–533. [Google Scholar] [CrossRef]

[12] M. Mohsin Butt, Ghazanfar Latif," Multi-channel Convolutions Neural Network Based Diabetic Retinopathy Detection from Fundus Images", 16th International Learning & Technology Conference 2019, Procedia Computer Science 163 (2019) 283–291.

[13] Nagaraja Gendler, 1Dharmendra Singh Rajput, 2Kuruva Lakshmanna," Enhancement of Detection of Diabetic Retinopathy Using Harris Hawks Optimization with Deep Learning Model", Hindawi Computational Intelligence and Neuroscience Volume 2022, Article ID 8512469, doi: https://doi.org/10.1155/2022/8512469

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