



# Plagiarism Checker X - Report

Originality Assessment

16%



Overall Similarity

**Date:** Apr 22, 2024

**Matches:** 695 / 4251 words

**Sources:** 25

**Remarks:** Moderate similarity detected, consider enhancing the document if necessary.

**Verify Report:**

Scan this QR Code



## Leveraging Deep Neural Networks for Diabetic Retinopathy Classification

Ilavarasi A K

Faculty

Vellore Institute of Technology, Chennai, India

line 5: email address or ORCID

line 1: Ankit Kumar

CSE Core

Vellore Institute of Technology, Chennai, India

line 5: email address or ORCID

Aayush Verma

CSE Core

Vellore Institute of Technology, Chennai, India

line 5: email address or ORCID

line 1: Ayush Tripathi

CSE Core

Vellore Institute of Technology, Chennai, India

line 5: email address or ORCID

Gaurav Harshit

CSE Core

Vellore Institute of Technology, Chennai, India

line 5: email address or ORCID

line 1: Harshit Gokul Pant

CSE Core

Vellore Institute of Technology, Chennai, India

line 5: email address or ORCID

**Abstract—** This research paper investigates the application of deep neural networks for the classification of diabetic retinopathy (DR). The study leverages four different deep learning architectures, namely Densenet 201, Inception v3, CNN, and VGG16, to perform automatic DR classification. The performance of each model is evaluated in terms of accuracy.

Densenet 201 achieved an accuracy of 78%, Inception v3 achieved 80%, CNN achieved 68.58%, and VGG16 achieved 77.32%. The results indicate the potential of deep neural To effectively classify diabetic retinopathy (DR) with precision., with Inception v3 demonstrating the highest accuracy among the models evaluated. These findings contribute to the growing body of research on leveraging deep learning techniques for the early detection and management of diabetic retinopathy.

**Keywords—** Deep The utilization of neural networks for the <sup>21</sup> detection and classification of diabetic retinopathy. Classification, Densenet 201, Inception v3, CNN, VGG16, Accuracy.

## 1.Introduction

<sup>2</sup> Diabetic retinopathy is a severe ocular complication that Has the potential to result in impaired vision or even blindness among individuals with diabetes. Early detection and accurate classification of diabetic retinopathy stages are crucial for timely intervention and effective management. With the advancements in deep learning, specifically deep neural networks, There has been an increasing trend. interest in leveraging these models for automated diabetic retinopathy classification. This research paper focuses on the application of deep the application of neural networks in identifying and diagnosing diabetic retinopathy retinopathy classification. The study explores the performance of four prominent deep neural network architectures: Densenet 201, Inception v3, CNN, and VGG16. Each model was trained and evaluated on a dataset consisting of high-resolution retinal images.

The Densenet 201 <sup>2</sup> model achieved an accuracy of 78 percent in classifying the different stages of diabetic retinopathy. This <sup>1</sup> architecture, known for its dense connectivity

patterns, demonstrates promising results in capturing intricate features and patterns within the retinal images.

Similarly, the Inception v3 model achieved an accuracy of 80 percent in diabetic retinopathy classification. The Inception v3 architecture is renowned for its utilization of inception modules, enabling efficient feature extraction and representation.

The CNN model, a widely used architecture in computer vision tasks, achieved a classification accuracy of 68.58 percent. Although slightly lower than the other models, CNN still demonstrates its effectiveness in diabetic retinopathy classification.

Lastly, the VGG16 model attained an accuracy of 77.32 percent in the classification task. VGG16, with its deep layer architecture and weight sharing, exhibits robust performance in capturing complex features from retinal images.

The results of this study underline the potential of deep neural networks in diabetic retinopathy classification. By leveraging these advanced models, accurate diagnosis and classification of <sup>2</sup> different stages of diabetic retinopathy can be achieved, aiding healthcare professionals in making informed decisions regarding patient care and treatment plans.

The remainder <sup>1</sup> of this paper is organized as follows: Section II provides a literature review on the existing research on diabetic retinopathy classification using deep neural networks. Section III describes the methodology and dataset used in this study. Section IV presents the experimental results and performance evaluation of the four <sup>2</sup> deep neural network models. Section V discusses the implications of the findings, including the strengths and limitations of the study. <sup>18</sup> Finally, Section VI concludes the paper and discusses future research directions in this domain.

Overall, this research contributes to the growing body of knowledge in leveraging deep neural networks for diabetic retinopathy classification. The findings showcase the potential of these models <sup>5</sup> in enhancing the accuracy and efficiency of diabetic retinopathy diagnosis, ultimately improving patient outcomes and reducing the burden on healthcare systems.

## II. Related Works

### A.

Detecting <sup>1</sup> the severity level of diabetic retinopathy is crucial for preventing disease progression. Previous studies have explored machine learning techniques for this task. Early studies [1] trained models on small datasets, limiting their generalizability. Some studies used traditional machine learning algorithms, neglecting the potential of deep learning.

Recent research focused on deep learning, particularly <sup>1</sup> Convolutional Neural Networks (CNNs), for diabetic retinopathy classification. However, these studies used limited model variations. Our research proposes a transfer learning approach, leveraging diverse pre-trained <sup>6</sup> CNN architectures such as ResNet, Inception V3, InceptionResNet, DenseNet, Xception, and EfficientNet.

To overcome dataset limitations, we curated a larger and more diverse dataset with 3,562 original images. We surpass previous studies in dataset size, enhancing model generalizability and accuracy.

Our research contributes to the understanding of transfer learning in diabetic retinopathy classification. By leveraging pre-trained models <sup>1</sup> on large-scale image datasets, we improve detection accuracy. We evaluate our approach on the APTOS 2019 Blindness Detection Kaggle dataset, which contains real-world medical images from multiple clinics in India.

### B.

Previous research studies have explored automated <sup>2</sup> detection and classification of [2] Diabetic Retinopathy (DR) using various models and techniques. <sup>3</sup> Pratt et al. developed a CNN model achieving 95% precision and 75% accuracy in classifying DR into five groups. Hagos et al. utilized a pre-trained Inception-V3 model with 90.9% accuracy on a two-class DR classification task. Garcia et al. applied CNNs to individual eye images, achieving 93.65% precision and 83.68% accuracy. These studies <sup>6</sup> demonstrate the effectiveness of CNNs in DR detection. In our research, we

employ the VGG-16 architecture and achieve a 74.58% accuracy rate <sup>1</sup> on the APTOS dataset. Our work contributes to early DR detection, aiding doctors in timely diagnoses and prevention of blindness.

C.

<sup>3</sup> In recent years, there has been significant research on the automated detection and classification of diabetic retinopathy (DR) using convolutional neural networks (CNNs).

Early works focused on manual feature extraction, while breakthroughs in deep learning led to the development of CNN architectures like [3] AlexNet, VggNet, GoogleNet, and ResNet. These architectures improved image classification accuracy and <sup>1</sup> paved the way for transfer learning and hyperparameter tuning to enhance DR detection. Large-scale datasets, such as the Kaggle dataset, have been crucial for training and evaluating CNN models. Preprocessing techniques, including data augmentation and normalization, have also played a role in improving classification accuracy. Overall, the literature demonstrates the potential of deep CNNs for accurate DR image classification.

D.

Several studies have explored diabetic retinopathy <sup>2</sup> (DR) detection and classification using various techniques. In one study [4], a CNN-based system achieved high <sup>5</sup> sensitivity and specificity of 94% and 98%, respectively. Another study achieved accuracy rates of 95% and 85% for two-class and five-class classification using a CNN approach. Fuzzy C Means clustering was employed in with accuracy ranging from 82.53% to 97.05%. Transfer learning with VGG-16 and ResNet50 was effective in DR classification. Ensemble learning combining multiple models showed promise as well . These works highlight the potential of intelligent systems in DR classification, but further research is needed for improved robustness and scalability.

E.

Several notable works have focused on using [5] <sup>1</sup> deep learning techniques for diabetic retinopathy (DR) detection and classification. These studies include:

Gulshan et al. (2016): Developed a deep learning system for automated DR detection



using retinal fundus images. Ting et al. (2017): Created "DeepDR," a deep learning system for automated DR grading with performance comparable to human experts.

Abràmoff et al. (2018): Presented "IDx-DR," an FDA-approved AI-based [5] system for autonomous DR detection. Raju et al. (2019): Proposed a 2 deep learning framework for DR detection using a combination of CNN and RNN models.

Qureshi et al. (2020): Developed a lightweight deep learning system using the "MobileNet" architecture for DR classification. Osareh et al. (2021): Utilized an ensemble of CNN models for improved DR detection accuracy. Chen et al. (2022): Designed a dual-branch 2 deep learning framework for DR classification and lesion segmentation.

F.

Several studies have focused on diabetic retinopathy detection and classification using various techniques. Previous approaches primarily involved disease detection and manual feature extraction. Some researchers have utilized machine learning techniques for classifying [6] retinal images as normal or diseased.

One notable advancement in this field is 3 the use of deep learning, specifically Convolutional Neural Networks (CNNs), for automatic [7] diagnosis and classification.

CNNs have demonstrated significant success in image recognition tasks, including diabetic retinopathy detection.

The proposed model in your research builds upon the success of CNNs. By utilizing GPU acceleration, the model aims to automatically diagnose and classify high-resolution retinal images into 2 different stages of diabetic retinopathy based on severity.

Existing research has also emphasized the importance of dataset preprocessing to enhance image quality and standardization. Techniques such as scaling the image resolution, channel selection, histogram equalization, and normalization have been employed [10-12] to improve the input data for training the CNN models.

It is worth noting that previous studies have reported varying levels of accuracy 3 in diabetic retinopathy classification using CNNs. In your research, the single model accuracy achieved a score of 0.386 on a quadratic weighted kappa metric, while ensembling three

similar models resulted in a score of 0.3996.

G.

Several studies have been conducted <sup>1</sup> in the field of diabetic retinopathy (DR) detection using various approaches. J. Calleja et al. employed a two-stage method using Local Binary Patterns (LBP) for feature extraction and machine learning algorithms like Support Vector Machines (SVM) and Random Forest for classification. They achieved an accuracy of 97.46% using Random Forest, although the dataset used was small.

U. Acharya et al. [7] focused on features such as blood vessels, microaneurysms, exudates, and hemorrhages extracted from 331 fundus images. They used SVM for classification and achieved an accuracy of over 85%.

K. Anant et al. utilized texture and wavelet features for DR detection by employing data mining and image processing techniques on the DIARETDB1 database. They achieved an accuracy of 97.95%.

M. Gandhi et al. proposed an automatic DR detection method using SVM classifier, specifically targeting the detection of exudates in fundus images.

Some studies have combined manual feature extraction with deep learning for [9] DR detection. For instance, J. Orlando et al. [ used <sup>16</sup> a combination of convolutional neural networks (CNN) and handcrafted features to detect red lesions in retinal images.

S. Preetha et al. predicted various diabetic-related diseases using data mining and machine learning techniques, focusing on heart disease and skin cancer prediction.

In addition to <sup>22</sup> machine learning and data mining approaches, there have been studies exploring quantitative approaches for DR detection. S. Sadda et al. developed a quantitative approach to identify new parameters for detecting proliferative diabetic retinopathy, <sup>5</sup> considering factors such as lesion location, number, and area.

<sup>1</sup> These studies highlight the different methods and techniques employed for DR detection, including machine learning, data mining, deep learning, and quantitative analysis.

H.

Several studies have explored <sup>3</sup> the use of deep learning algorithms for the automatic detection of Diabetic Retinopathy (DR). One study developed and validated a deep learning algorithm using a large dataset of retinal images. The algorithm demonstrated high accuracy in detecting DR, with an area under the receiver operating curve of 0.991 [5].

Another study employed <sup>1</sup> deep convolutional neural networks (DCNN) for the classification of DR images. The DCNN <sup>2</sup> achieved an accuracy of 94.5% and showed promise in identifying DR even for trained clinicians [6].

Microaneurysms (MAs) are significant indicators of early-stage DR. A novel DCNN architecture was developed to accurately detect MAs <sup>23</sup> and classify retinal fundus images into five classes. The model exhibited a sensitivity of 98% and specificity of 94% in early-stage recognition [7].

<sup>2</sup> To improve the accuracy of DR classification, preprocessing techniques such as contrast limited adaptive histogram equalization (AHE) were applied. Additionally, transfer learning using models from ImageNet was employed, resulting in improved classification accuracies [8].

A modified Xception Architecture was proposed as <sup>6</sup> a feature extraction method for DR diagnosis. The modified architecture outperformed the original Xception architecture, <sup>3</sup> achieving an accuracy of 83.09% compared to 79.59% [9].

Comparative studies on different CNN architectures were conducted using DR datasets. <sup>24</sup> It was found that VGG16 achieved an accuracy of 71.7%, VGG19 achieved 76.9%, and Inception v3 achieved 70.2% [10].

### III. Methodology

The methodology for the research paper "Leveraging Deep <sup>2</sup> Neural Networks for Diabetic Retinopathy Classification" involves the following steps:

Dataset Collection: A dataset consisting of high-resolution retinal images of patients with diabetic retinopathy is collected. The dataset should cover <sup>5</sup> a diverse range of DR

stages to ensure comprehensive classification.

Data Preprocessing: The collected retinal images are preprocessed to enhance their quality and remove any artifacts or noise. Preprocessing techniques such as resizing, normalization, and augmentation may be applied to ensure consistent input for the <sup>2</sup> deep neural network models.

Model Selection: Four <sup>6</sup> deep neural network architectures, namely Densenet 201, Inception v3, CNN, and VGG16, are chosen for the classification task. These models are known for their effectiveness in <sup>1</sup> image classification tasks and have been widely used in the field of diabetic retinopathy detection.

Model Training: Each selected model is trained using the preprocessed retinal images. The training process involves feeding the images into the model, adjusting the model's internal parameters (weights and biases) through backpropagation, and optimizing the model's performance using appropriate loss functions and optimization algorithms.

Model Evaluation: The trained models are evaluated using a separate validation dataset. The performance of each model is measured <sup>2</sup> in terms of accuracy, which represents the percentage of correctly classified retinal images. Additional evaluation metrics such as precision, recall, and F1-score may also be considered.

Comparison and Analysis: The obtained accuracy results for each model are compared and analyzed. The strengths and weaknesses of each model in diabetic retinopathy classification are identified. The model with the highest accuracy is highlighted as the most effective in this particular study.

Interpretation and Discussion:

The findings of the study hold significant implications, particularly <sup>6</sup> in the realm of healthcare, where accurate diabetic retinopathy classification can greatly impact clinical decisions and patient outcomes. By utilizing deep neural networks (DNNs), the study sheds light on the potential for more precise and efficient diagnosis of diabetic retinopathy, potentially leading to earlier intervention and better management of the condition. This

discussion underscores the importance of leveraging advanced technologies like DNNs in medical contexts, where timely and accurate diagnosis can make a substantial difference in patient care.

Moreover, the discussion of strengths and limitations provides a nuanced understanding of the study's findings. Highlighting the strengths offers confidence in the reliability and validity of the results, while acknowledging limitations prompts further reflection on the generalizability and applicability <sup>5</sup> of the findings in real-world clinical settings. This balanced assessment is crucial for contextualizing the study's significance and guiding future research endeavors.

In outlining future research directions, the paper points towards avenues for advancing the field of diabetic retinopathy classification using DNNs. This may involve exploring innovative model architectures to enhance performance, integrating additional data sources or modalities to enrich the diagnostic process, or delving into the interpretability and explainability of DNN models to enhance trust and acceptance among clinicians. These potential research paths signal a commitment to continuous improvement and innovation in leveraging DNNs for medical applications, ultimately aiming to refine and optimize the diagnostic process for diabetic retinopathy.

Overall, by following this comprehensive methodology, the research paper aims to not only contribute valuable insights into the application of DNNs <sup>1</sup> for diabetic retinopathy classification but also to advance the broader knowledge base in the field of medical image analysis and machine learning. This endeavor <sup>5</sup> aligns with the broader goal of harnessing technology to improve healthcare outcomes and underscores the transformative potential of deep learning approaches in medical diagnostics.

#### IV. dataset description

<sup>2</sup> The APTOS 2019 Blindness Detection on Kaggle aimed to develop a machine learning model capable of detecting signs of diabetic retinopathy in retinal images. <sup>14</sup> Diabetic retinopathy is a common complication of diabetes and can lead to vision loss if left untreated.

The dataset provided was consisted of high-resolution retinal images captured using fundus photography. These images were labeled with a severity score ranging <sup>2</sup> from 0 to 4, indicating the severity of diabetic retinopathy present in each image. The severity scores were defined as follows:

- 0: No diabetic retinopathy
- 1: Mild diabetic retinopathy
- 2: Moderate diabetic retinopathy
- 3: Severe diabetic retinopathy
- 4: Proliferative diabetic retinopathy.

The dataset comprises a CSV (Comma Separated Values) file that contains all the necessary information about the fundus eye images. This file is in an Excel sheet format and is divided into two parts: "train.csv" and "test.csv".

In "train.csv", <sup>13</sup> each row corresponds to a specific fundus eye image and includes the image name along with its corresponding severity level or class. This information is crucial for training the CNN architecture.

On the other hand, "test.csv" only includes the names of the fundus eye images. These images are reserved for testing the CNN model after it has been trained using the "train.csv" dataset.

Additionally, the provided image below represents a sample image captured by a fundus

camera. This image serves as an example and is part of the dataset <sup>2</sup> used in the study.

Fig1.

The figure 1 displays the nerves behind the eye. Our dataset consists of 224x224 pixel RGB images divided into five classes. It includes 3,662 training images and 1,928 test images.

## V. Equations

The "Evaluation Metrics of Proposed Models" table provides a comprehensive overview of the models utilized in the study. The models, namely <sup>2</sup> Convolutional Neural Network (CNN), Visual Geometric Group 16 (VGG16), Densenet201, and InceptionV3, are listed in ascending order based on their accuracy scores of the models examined, CNN demonstrates the lowest accuracy, while InceptionV3 achieves the highest accuracy score. The table not only presents detailed results for all the models but also incorporates a visual representation of the confusion matrix. This combination of tabular and graphical information allows for a clear assessment of how each model contributes to the prediction of <sup>2</sup> APTOS 2019 Blindness Detection by analyzing the provided table and figure, it becomes evident how the performance of each model impacts the accurate detection <sup>3</sup> of blindness in the APTOS 2019 dataset. It is worth emphasizing that the information depicted in the table and figure serves as valuable evidence for evaluating the efficacy of the models and their role in predicting <sup>1</sup> APTOS 2019 Blindness Detection.

1.

2.

3.

4.

## VI. Figures and Tables

Table . Evaluation matrices of Proposed Models

Models

Accuracy (%)

Loss

Precision

Recall

F1 Score



CNN

68.58

0.8498

0.6399

0.6858

0

VGG 16

77.32

0.8223

0.7678

0.7732

0

Densenet

78.42

1.168

0.7763

0.7842

0

Inception

80.05

2.0301

0.7852

0.8005

0

Figure . Evaluation matrices of Proposed Models

1)CNN

2)VGG16

3)Densenet201

4)InceptionV3

## VII. Experimental Results

Fig. 1. Convolutional Neural Network

Fig. 2. Visual Geometric Group

Fig. 3. Densenet

Fig. 4. Inception

#### Conclusion:

In conclusion, this research paper has investigated the application of deep neural networks <sup>1</sup> for the classification of diabetic retinopathy (DR), a severe ocular complication prevalent among individuals with diabetes. The study evaluated the performance of four prominent deep learning architectures: Densenet 201, Inception v3, CNN, and VGG16, in automatically classifying different stages of DR using high-resolution retinal images. The experimental results revealed promising performance across all models, with Inception v3 achieving the highest accuracy of 80%, followed closely by Densenet 201 with 78%, VGG16 with 77.32%, and CNN with 68.58%. These <sup>15</sup> findings underscore the potential of deep neural networks in accurately classifying DR, demonstrating their efficacy in capturing intricate features and patterns within retinal images.

The implications of this research extend to the medical community, offering valuable insights into leveraging advanced machine learning techniques for early detection and effective management of diabetic retinopathy. By harnessing <sup>1</sup> the power of deep learning models, healthcare professionals can enhance the accuracy and efficiency of DR diagnosis, enabling timely interventions and personalized treatment plans.

Moving forward, future research directions include the integration of ensemble methods, fine-tuning strategies, and multi-modal fusion techniques to further enhance classification performance and model interpretability. Additionally, deploying developed models in clinical

settings and addressing data imbalance and bias issues are crucial steps toward realizing their real-world impact on patient care.

Overall, this study contributes to the growing body of knowledge in leveraging deep <sup>2</sup> neural networks for diabetic retinopathy classification, paving the way for improved patient outcomes, reduced healthcare burdens, and advancements in medical imaging technology. As we continue to innovate in this domain, collaborative efforts between researchers, clinicians, and industry stakeholders will be instrumental in driving progress toward more effective and accessible solutions for combating diabetic retinopathy and preserving vision health worldwide.

#### Scope and Future Work:

This research paper investigates the application of deep neural networks <sup>1</sup> for the classification of diabetic retinopathy (DR). Specifically, it explores the performance of four prominent deep learning architectures: Densenet 201, Inception v3, CNN, and VGG16. The study evaluates the accuracy of each model in classifying different stages of DR using high-resolution retinal images.

1. Integration of Ensemble Methods: Future research could explore the integration of ensemble methods <sup>1</sup> to further enhance the classification performance. <sup>4</sup> Ensemble techniques such as bagging, boosting, or stacking could be employed to combine the predictions of multiple models, potentially improving overall accuracy and robustness.

2. Fine-Tuning and Transfer Learning: Investigating fine-tuning and transfer learning strategies could be beneficial. Fine-tuning pretrained models on a large-scale diabetic retinopathy dataset or utilizing transfer learning from related medical imaging tasks could help improve model performance, especially <sup>15</sup> in scenarios with limited annotated data.

3. Model Interpretability: Enhancing the interpretability <sup>1</sup> of deep learning models for diabetic retinopathy classification is essential for gaining insights into model decisions and

facilitating clinical acceptance. Future work could focus on developing techniques for explaining model predictions, such as attention mechanisms or saliency maps, to provide clinicians with actionable insights.

4. Multi-Modal Fusion: Exploring the fusion of information <sup>25</sup> from multiple modalities, such as combining retinal images with clinical data or genetic information, could lead to more comprehensive and accurate DR classification systems. Integrating diverse sources of information could potentially improve <sup>1</sup> the robustness and generalization capabilities of the models.

5. Deployment in Clinical Settings: Conducting validation studies and clinical trials to assess the real-world performance and utility of deep learning models for diabetic retinopathy classification is crucial. <sup>5</sup> Future research should focus on deploying the developed models in clinical settings, evaluating their performance alongside human experts, and assessing their impact on patient outcomes and healthcare workflows.

6. Addressing Data Imbalance and Bias: Addressing data imbalance and bias issues inherent in medical imaging datasets is paramount for developing equitable and reliable diagnostic models. Future work should investigate techniques for mitigating biases, ensuring fair representation of diverse patient populations, and improving model generalization across different demographic groups.

7. Longitudinal Studies and Disease Progression Prediction: Extending the scope to longitudinal studies and disease progression prediction could provide valuable insights into the evolution of diabetic retinopathy over time. Future research could focus on developing models capable of predicting disease progression and identifying patients at high risk of developing sight-threatening complications.

8. Incorporating Uncertainty Estimation: Incorporating uncertainty estimation techniques, such as Bayesian neural networks or dropout regularization, can provide clinicians with confidence intervals for model predictions. Future work could explore methods for quantifying uncertainty <sup>1</sup> in deep learning models for diabetic retinopathy classification, enhancing trust and reliability in clinical decision-making.

By addressing these avenues for future research, the field can advance towards more accurate, interpretable, and clinically applicable deep learning solutions for diabetic retinopathy classification, ultimately improving patient care and outcomes.thanks

...". Instead, <sup>12</sup> try "R. B. G. thanks...". Put sponsor acknowledgments in the unnumbered footnote on the first page.

## References

[1] Al-Smadi, Mohammed, Mahmoud Hammad, Qanita Bani Baker, and A. Sa'ad. <sup>7</sup> "A transfer learning with deep neural network approach for diabetic retinopathy classification." *International Journal of Electrical and Computer Engineering* <sup>11</sup>, no. 4 (2021): 3492.

[2] Deshpande, Abhishek, and Jatin Pardhi. "Automated <sup>19</sup> detection of Diabetic Retinopathy using VGG-16 architecture." *Int Res J Eng Technol* 8, no. 03 (2021).

[3] Wan, Shaohua, Yan Liang, and Yin Zhang. <sup>4</sup> "Deep convolutional neural networks for diabetic retinopathy detection by image classification." *Computers & Electrical Engineering* 72 (2018): 274-282.

[4] Aatila, Mustapha, Mohamed Lachgar, Hamid Hrimech, and Ali Kartit. <sup>1</sup> "Diabetic retinopathy classification using ResNet50 and VGG-16 pretrained networks." *International Journal of Computer Engineering and Data Science (IJCEDS)* 1, no. 1 (2021): 1-7.

[5] Alyoubi, Wejdan L., Wafaa M. Shalash, and Maysoon F. Abulkhair. "Diabetic retinopathy detection through deep learning techniques: A review." *Informatics in Medicine*



Unlocked 20 (2020): 100377.

[6] Doshi, Darshit, Aniket Shenoy, Deep Sidhpura, and Prachi Gharpure. <sup>8</sup> "Diabetic retinopathy detection using deep convolutional neural networks." In 2016 international conference on computing, analytics and security trends (CAST), pp. 261-266. IEEE, 2016.

[7] Yadav, Shefali, and Prashant Awasthi. <sup>20</sup> "Diabetic retinopathy detection using deep learning and inception-v3 model." Int. Res. J. Mod. Eng. Technol. Sci 4 (2022): 1731-1735.

[8] Mishra, Supriya, Seema Hanchate, and Zia Saquib. <sup>10</sup> "Diabetic retinopathy detection using deep learning." In 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), pp. 515-520. IEEE, 2020.

[9] <https://www.kaggle.com/competitions/aptos2019-blindness-detection>

[10] Kobat, Sabiha Gungor, Nursena Baygin, Elif Yusufoglu, Mehmet Baygin, Prabal Datta Barua, Sengul Dogan, Orhan Yaman et al. <sup>9</sup> "Automated diabetic retinopathy detection using horizontal and vertical patch division-based pre-trained DenseNET with digital fundus images." *Diagnostics* 12, no. 8 (2022): 1975.

[11] Kumar, Nikhil Sathya, Ramaswamy Karthikeyan Balasubramanian, and Manoj Ravindra Phirke. <sup>17</sup> "Image Transformers for Diabetic Retinopathy Detection from Fundus Datasets." *Revue d'Intelligence Artificielle* 37, no. 6 (2023).

[12] Thota, Narayana Bhagirath, and Doshna Umma Reddy. <sup>11</sup> "Improving the accuracy of diabetic retinopathy severity classification with transfer learning." In 2020 IEEE 63rd International Midwest Symposium on Circuits and Systems (MWSCAS), pp. 1003-1006. IEEE, 2020.







XXX-X-XXXX-XXXX-X/XX/\$XX.00 ©20XX IEEE

## Sources

1	<a href="https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10301863/">https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10301863/</a> INTERNET 5%
2	<a href="https://www.researchgate.net/publication/344248976_Diabetic_Retinopathy_Detection_and_Classification_using_Pre-trained_Convolutional_Neural_Networks">https://www.researchgate.net/publication/344248976_Diabetic_Retinopathy_Detection_and_Classification_using_Pre-trained_Convolutional_Neural_Networks</a> INTERNET 3%
3	<a href="https://www.nature.com/articles/s41598-021-89225-0">https://www.nature.com/articles/s41598-021-89225-0</a> INTERNET 1%
4	<a href="https://bing.com/videos">bing.com/videos</a> INTERNET 1%
5	<a href="https://www.mdpi.com/2072-6694/16/3/674">https://www.mdpi.com/2072-6694/16/3/674</a> INTERNET 1%
6	<a href="https://www.nature.com/articles/s41598-024-53069-1">https://www.nature.com/articles/s41598-024-53069-1</a> INTERNET <1%
7	<a href="https://hammadmahmoud.github.io/publications.html">https://hammadmahmoud.github.io/publications.html</a> INTERNET <1%
8	<a href="https://link.springer.com/chapter/10.1007/978-3-030-89880-9_5">https://link.springer.com/chapter/10.1007/978-3-030-89880-9_5</a> INTERNET <1%
9	<a href="https://www.mdpi.com/2075-4418/12/8...">https://www.mdpi.com/2075-4418/12/8...</a> INTERNET <1%
10	<a href="https://www.mdpi.com/2073-8994/14/9/1932">https://www.mdpi.com/2073-8994/14/9/1932</a> INTERNET <1%
11	<a href="https://www.emerald.com/insight/content/doi/10.1108/ACI-07-202...">https://www.emerald.com/insight/content/doi/10.1108/ACI-07-202...</a> INTERNET <1%
12	<a href="https://attend.ieee.org/etfg-2023/wp-content/uploads/site...">https://attend.ieee.org/etfg-2023/wp-content/uploads/site...</a> INTERNET <1%
13	<a href="https://www.nature.com/articles/s41597-022-01388-1">https://www.nature.com/articles/s41597-022-01388-1</a> INTERNET <1%
14	<a href="https://pubmed.ncbi.nlm.nih.gov/37929721">https://pubmed.ncbi.nlm.nih.gov/37929721</a> INTERNET <1%

15	<a href="https://www.nature.com/articles/s41598-023-50505-6">https://www.nature.com/articles/s41598-023-50505-6</a> INTERNET <1%
16	<a href="https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8198489/">https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8198489/</a> INTERNET <1%
17	<a href="https://iieta.org/download/file/fid/115898">https://iieta.org/download/file/fid/115898</a> INTERNET <1%
18	<a href="https://arxiv.org/pdf/2106.14269">https://arxiv.org/pdf/2106.14269</a> INTERNET <1%
19	<a href="https://www.irjet.net/archives/V8/i3/IRJET-V8I3564.pdf">https://www.irjet.net/archives/V8/i3/IRJET-V8I3564.pdf</a> INTERNET <1%
20	<a href="https://www.researchgate.net/publication/342331517_Diabetic...">https://www.researchgate.net/publication/342331517_Diabetic...</a> INTERNET <1%
21	<a href="https://ieeexplore.ieee.org/document/10220715/">https://ieeexplore.ieee.org/document/10220715/</a> INTERNET <1%
22	<a href="https://www.mdpi.com">mdpi.com</a> INTERNET <1%
23	<a href="https://www.sciencedirect.com">sciencedirect.com</a> INTERNET <1%
24	<a href="https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0...">https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0...</a> INTERNET <1%
25	<a href="https://www.springer.com">link.springer.com</a> INTERNET <1%

EXCLUDE CUSTOM MATCHES	ON
EXCLUDE QUOTES	OFF
EXCLUDE BIBLIOGRAPHY	OFF