AG Salud. 2025; 3:197
doi: 10.62486/agsalud2025197

ORIGINAL

Diabetic Detection from Images of the Eye

Detección de la diabetes a partir de imágenes del ojo

Arepalli Gopi[1], Sudha L.R[2], Iwin Thanakumar Joseph S[3]

[1]Research Scholar, Department of Computer Science & Engineering, Annamalai University, Chidambaram, Tamilnadu, India.
[2]Associate Professor, Department of Computer Science & Engineering, Annamalai University, Chidambaram, Tamilnadu, India.
[3]Associate Professor, Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India.

Cite as: Gopi A, Sudha L, Iwin Thanakumar JS. Diabetic Detection from Images of the Eye. AG Salud. 2025; 3:197. https://doi.org/10.62486/agsalud2025197

Submitted: 26-04-2024 **Revised:** 13-07-2024 **Accepted:** 04-11-2024 **Published:** 01-01-2025

Editor: Telmo Raúl Aveiro-Róbalo

Corresponding author: Arepalli Gopi

ABSTRACT

This cross-sectional study aims to detect Diabetic Retinopathy (DR) in patients who have had retinal scans and ophthalmological exams. The research makes use of tailored retinal images together with the OPF (Optimum-Path Forest) and RBM (Restricted Boltzmann Machine) models to categorize images according to the presence or absence of DR. In this work, features were extracted from the retinal images using both the RBM and OPF models. In particular, after a thorough system training phase, RBM was able to extract between 500 and 1000 features from the images. The study included fifteen distinct trial series, each with thirty cycles of repetition. The research comprised 122 eyes, or 73 diabetic patients, with a gender distribution that was reasonably balanced and an average age of 59,7 years. Remarkably, the RBM-1000 model stood out as the top performer, with the highest overall accuracy of 89,47 % in diagnosis. In terms of specificity, the RBM-1000 and OPF-1000 models surpassed the competition, correctly categorizing all images free of DR symptoms. These findings highlight the potential of machine learning, particularly the RBM model, for self-identifying illnesses. The potential of machine learning models—in particular, RBM and OPF—to automate the diagnosis of diabetic retinopathy is demonstrated by this work. The results show how well the RBM model diagnoses, how sensitive it is, and how well it can be applied for efficient DR screening and diagnosis. This information may be used to improve the effectiveness of systems that identify retinal illnesses.

Keywords: CNN; Feature Extraction; Localization; Segmentation; Region of Interest; Irido-Diagnosis.

RESUMEN

Este estudio transversal pretende detectar la Retinopatía Diabética (RD) en pacientes que se han sometido a exploraciones retinianas y exámenes oftalmológicos. La investigación hace uso de imágenes de retina adaptadas junto con los modelos OPF (Optimum-Path Forest) y RBM (Restricted Boltzmann Machine) para categorizar las imágenes según la presencia o ausencia de RD. En este trabajo, se extrajeron características de las imágenes retinianas utilizando los modelos RBM y OPF. En concreto, tras una exhaustiva fase de entrenamiento del sistema, RBM fue capaz de extraer entre 500 y 1000 características de las imágenes. El estudio incluyó quince series de ensayos distintas, cada una con treinta ciclos de repetición. En la investigación participaron 122 ojos, es decir, 73 pacientes diabéticos, con una distribución de sexos razonablemente equilibrada y una edad media de 59,7 años. Sorprendentemente, el modelo RBM-1000 destacó como el de mayor rendimiento, con una precisión global del 89,47 % en el diagnóstico. En términos de especificidad, los modelos RBM-1000 y OPF-1000 superaron a la competencia, categorizando correctamente todas las imágenes libres de síntomas de RD. Estos resultados ponen de relieve el potencial del aprendizaje automático, en particular del modelo RBM, para la autoidentificación de enfermedades. Este trabajo demuestra el potencial

© 2025; Los autores. Este es un artículo en acceso abierto, distribuido bajo los términos de una licencia Creative Commons (https://creativecommons.org/licenses/by/4.0) que permite el uso, distribución y reproducción en cualquier medio siempre que la obra original sea correctamente citada

de los modelos de aprendizaje automático -en particular, RBM y OPF- para automatizar el diagnóstico de la retinopatía diabética. Los resultados muestran lo bien que diagnostica el modelo RBM, lo sensible que es y lo bien que puede aplicarse para un cribado y diagnóstico eficientes de la RD. Esta información puede utilizarse para mejorar la eficacia de los sistemas que identifican enfermedades de la retina.

Palabras clave: CNN; Extracción de Características; Localización; Segmentación; Región de Interés; Irido-Diagnóstico.

INTRODUCTION

Diabetic Retinopathy (DR) is a frequent and significant medical condition that puts the visual health of people with diabetes at considerable risk worldwide. As the leading cause of preventable blindness in people of working age, it emphasizes the urgent need for early detection and treatment. Since DR frequently progresses without symptoms until it is in an advanced stage, early detection is essential to preventing irreversible vision loss. Several European countries have developed effective early detection programs that evaluate retinal images by combining state-of-the-art technology with the expertise of medical professionals. For example, in 2007 and 2008, the United Kingdom evaluated approximately 1,7 million diabetes individuals for DR, demonstrating the practicality and importance of wide screening initiatives. As part of its “Eye check” program, the Netherlands has been routinely evaluating over 30 000 individuals with diabetes since the early 2000s, much like the United States.

Over the past 10 years, substantial advancements in computer vision techniques have been achieved in artificial intelligence (AI), which has revolutionized the study of retinal imagery. By enhancing the interpretation of retinal images, these techniques hope to contribute to the development of highly accurate models for the early detection and classification of DR. This introduction establishes the importance of DR as a major health concern and highlights the need for early detection as well as the application of cutting-edge technology, such as artificial intelligence and computer vision, to achieve this goal. The next sections of this article will go into further detail on the history, risk factors, and development of a deep learning model that utilizes retinal images to classify and rate the severity of diabetic retinopathy.

High blood sugar levels can damage the tiny blood vessels in the eyes, a disease known as diabetic retinopathy. This disease weakens the circulatory system of the retina, the tissue at the back of the eye that responds to light. This results in a variety of vascular abnormalities. Hemorrhages, microaneurysms, and soft and hard fluid exudates are a few of these changes. Distorted artery borders cause microaneurysms, which appear as tiny red spots on the retina. On the other hand, hemorrhages are caused by blood leaking from damaged arteries and manifest as dark red patches. White lesions caused by arteriole blockage are known as soft exudates, while yellow, waxy patches caused by blood leaking from arteries are known as hard exudates. Diabetic retinopathy may be classified into two main types: proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR). The NPDR, which is the forerunner of DR, may be divided into three subtypes: mild, moderate, and severe. Growth of abnormal blood vessels inside the retina, which might rupture and leak and cause significant vision loss, is a sign of an advanced stage of PDR.

As the condition progresses, there may be an increased risk of damage to the macula, a central region of the retina that is crucial for sharp, center vision. When diabetic retinopathy damages the macula, the condition known as diabetic macular edema (DME) occurs. A accumulation of fluid in the macula, which causes swelling and worsens vision, is a characteristic of DME.

This work focuses on the creation of a deep learning model that can effectively categorize people based on the existence and severity of diabetic retinopathy in light of these difficulties and the crucial relevance of early detection. Our goal is to give healthcare professionals a powerful tool to quickly detect and classify people at danger, permitting prompt intervention and maybe saving their vision. We will do this by utilizing a dataset collecting retinal pictures. In order to improve the early diagnosis and management of diabetic retinopathy, a condition that affects millions of people worldwide and continues to be a leading cause of avoidable blindness, this study represents a significant advancement in utilizing the power of artificial intelligence and computer vision. In the parts that follow, we’ll examine the methods.

The escalating prevalence of diabetes and its concomitant complications amplifies the urgency to develop sophisticated tools capable of furnishing swift and accurate diagnoses. Against this backdrop, the integration of machine learning techniques, particularly CNNs, emerges as a promising avenue for enhancing the precision and efficiency of DR identification. Subsequent sections of this introduction will expound upon the rationale behind selecting CNNs, with a specialized focus on the VGG-16 architecture, as a means to address the intricate nuances of DR diagnosis in customized retinal imagery.

https://doi.org/10.62486/agsalud2025197

CNN Algorithm Overview

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for processing structured grid-like data, with a primary application in computer vision. Developed with inspiration from the human visual system, CNNs have revolutionized the field of image analysis and recognition. They are known for their ability to automatically learn and recognize complex patterns and features within images, making them a powerful tool for various tasks, including diabetes detection.

At the heart of a CNN lies the convolutional layer, which plays a central role in the algorithm. This layer is responsible for scanning the input image with a set of learnable filters (kernels). These filters convolve over the image, computing dot products at each location, which helps detect local patterns or features. By stacking multiple convolutional layers, a CNN can capture hierarchical representations of an image, from low-level edges and textures to high-level object parts and structures

Another key component of CNNs is the pooling layer, often referred to as subsampling or max-pooling. This layer reduces the spatial dimensions of the feature maps produced by the convolutional layers while retaining the most important information. Pooling helps make the network more robust to variations in object position and scale, and it reduces the number of parameters, which is crucial for preventing overfitting

The effectiveness of Convolutional Neural Networks (CNNs) in diabetic disease detection and other medical imaging tasks can be attributed to their capability to autonomously learn pertinent features from data. This makes CNNs highly proficient in tasks such as image classification, object detection, and segmentation in the context of diabetic disease diagnosis. In this research, we delve into the application of CNNs, with a particular emphasis on the VGG-16 and VGG-19 architectures, to optimize diabetic disease detection systems. The primary goal is to improve the accuracy and reliability of these systems in identifying and classifying diabetic retinopathy stages or severity levels from retinal images. This adaptation of CNNs for diabetic disease detection involves leveraging their ability to automatically extract and understand relevant features, ultimately enhancing the performance of the diagnostic system in the medical domain.

Working Of CNN

In the realm of diabetic disease detection, Convolutional Neural Networks (CNNs) stand out as powerful tools for the automated analysis of retinal images. Tailored to capture spatial hierarchies and intricate features within medical images, CNNs are well-suited for discerning patterns associated with diabetic retinopathy. The workflow of a CNN designed for diabetic disease detection follows a systematic process, starting with the input layer receiving raw retinal image data. Convolutional layers then extract localized features indicative of diabetic retinopathy, such as lesions or microaneurysms. Activation functions, incorporating Rectified Linear Units (ReLUs), introduce non-linearity to capture complex relationships. Subsequent pooling layers downsample feature maps, maintaining crucial information. As the network progresses, it constructs a hierarchical representation of the input, emphasizing features relevant to diabetic retinopathy.

The adaptability of CNNs to diverse retinal scenarios and their automatic learning capabilities make them invaluable in advancing diagnostic systems for diabetic diseases. The fully connected layers act as potent classifiers, discerning intricate patterns and relationships within retinal images and producing output indicating the presence or severity of diabetic retinopathy. Training involves parameter optimization through backpropagation and gradient descent, with the potential application of transfer learning for enhanced feature recognition. The success of the CNN hinges on the diversity and quality of the training dataset, encompassing various stages of diabetic retinopathy and image conditions.

Moreover, techniques such as data augmentation further improve model robustness by artificially expanding the dataset. Applying transformations like rotation, scaling, and flipping introduces variations that enhance the model's ability to generalize to unseen retinal scenarios. This augmentation not only aids in capturing a wider range of diabetic retinopathy characteristics but also contributes to the network's resilience to diverse imaging conditions.

In a clinical context, the deployment of CNNs for diabetic disease detection holds promise for early and accurate diagnosis, allowing for timely intervention to prevent or mitigate the progression of diabetic retinopathy. As technology continues to advance, the integration of CNNs into medical imaging systems opens avenues for more efficient and reliable diabetic disease screening on a broader scale. The continuous refinement of CNN architectures and training methodologies ensures that these models stay at the forefront of innovation in the ever-evolving field of medical image analysis for diabetic diseases.

VGG-16

The VGG-16 architecture, a prominent convolutional neural network (CNN) in computer vision and deep learning, has been instrumental in image classification tasks. As a member of the Visual Geometry Group (VGG) family developed by the University of Oxford, VGG-16 is renowned for its simplicity, depth, and impressive performance. With its 16 weight layers, including 13 convolutional layers and 3 fully connected layers, VGG-

https://doi.org/10.62486/agsalud2025197

16 is adept at extracting features from input images across various spatial scales. The architecture's depth, coupled with the use of small 3x3 convolutional filters, allows it to capture intricate details, starting from low-level edges and textures to higher-level semantic information.

A distinguishing feature of VGG-16 lies in its use of small-sized convolutional filters, each with a fixed kernel size of 3x3 pixels, complemented by max-pooling layers. The employment of 3x3 filters facilitates a detailed examination of input images, effectively capturing both fine-grained and high-level features. The incorporation of max-pooling layers then reduces the spatial dimensions of the feature maps while retaining crucial information, enhancing the network's robustness to variations in object position and scale.

The fully connected layers positioned towards the end of VGG-16 enable it to learn intricate combinations of features, making it effective in image classification tasks. These layers provide a pathway to map the extracted features to the final classification decision. In the context of image classification, VGG-16 has demonstrated state-of-the-art performance on various datasets, including the ImageNet Large Scale Visual Recognition Challenge, showcasing its ability to classify images into diverse object categories with remarkable accuracy.

In this research endeavor, we embark on exploring the potential application of VGG-16 in the domain of diabetic disease detection. By leveraging its depth and exceptional feature extraction capabilities, we aim to enhance its performance and adapt it to the specific task of identifying diabetic retinopathy in retinal images. The motivation behind this exploration is rooted in evaluating whether VGG-16, with optimizations and fine-tuning, can contribute to the development of more accurate and reliable diabetic disease detection systems. This adaptation involves tailoring the network to discern relevant features indicative of diabetic retinopathy, ultimately contributing to the advancement of diagnostic capabilities in the medical field.

Working Of VGG-16

To apply the VGG-16 architecture to diabetic detection using retinal images, the process involves repurposing the pre-trained model through transfer learning. Originally designed for general image recognition, VGG-16's 16-layer structure, which includes convolutional and fully connected layers, can be adapted to the specific task of identifying diabetic retinopathy. Initialization of the model with pre-trained weights on a diverse dataset, ideally comprising retinal images associated with various stages and severity levels of diabetic retinopathy, imparts valuable knowledge applicable to relevant visual patterns.

The adaptation begins by replacing the original output layer with a custom layer tailored to accommodate specific classes relevant to diabetic detection. These classes may represent different stages or severity levels of diabetic retinopathy. The subsequent fine-tuning process optimizes the model's weights using an appropriate loss function, such as categorical cross-entropy, and an optimization algorithm like stochastic gradient descent. Through iterative training, the model parameters are updated to enhance its ability to discern intricate features associated with diabetic retinopathy.

Training and evaluation take place on a dedicated dataset curated for diabetic detection from retinal images, ensuring that the model becomes adept at identifying relevant patterns indicative of the disease. The quality and representativeness of this dataset are pivotal for the model's performance. Additionally, considerations for data augmentation techniques, such as rotations, scaling, and flipping, can be applied to artificially expand the dataset, improving the model's generalization to diverse retinal scenarios.

Once trained, the adapted VGG-16 model can be deployed to predict the presence and severity of diabetic retinopathy in new, unseen retinal images. This approach harnesses the knowledge gained from pre-training on a diverse dataset, offering a robust solution for image-based diabetic detection. The success of this adaptation relies on meticulous tuning, a well-curated dataset, and thoughtful considerations of data augmentation strategies for enhanced model generalization in the specific context of diabetic retinopathy detection.

Performance Comparison

The question of which of these architectures performs better often depends on the specific task and dataset in question. VGG-19's increased depth allows it to potentially capture more intricate details, making it a strong candidate for tasks that require a deeper feature hierarchy. In scenarios where data is abundant and complexity is high, VGG-19 may outperform VGG-16.

However, it is worth noting that the deeper architecture of VGG-19 also comes with a computational cost. Training and inference with VGG-19 can be more resource-intensive than VGG-16. In cases where computational resources are limited or real-time performance is critical, VGG-16 may be the preferred choice due to its slightly lighter architecture.

Ultimately, the choice between VGG-16 and VGG-19 hinges on the specific requirements of the task at hand. It is essential to consider factors such as dataset size, task complexity, available computational resources, and the desired trade-off between accuracy and computational efficiency.

In the subsequent chapters of this research, we delve into the application of both VGG-16 and VGG-19 in the context of diabetes detection, aiming to determine which of these architectures, when optimized, yields better results for this specific task. The insights gained from this exploration will shed light on the relative

https://doi.org/10.62486/agsalud2025197

strengths and weaknesses of these two architectures, contributing to our understanding of their performance in diabetes detection applications.

Existing Algorithm

The landscape of Diabetic Retinopathy (DR) detection systems have witnessed a dynamic evolution fuelled by technological advancements and a growing understanding of medical image analysis. A thorough literature survey has illuminated the multifaceted approaches employed for identifying DR, providing a rich context for a critical examination of the current state-of-the-art methodologies.

Historically, DR detection relied heavily on manual assessment by clinicians, introducing subjectivity and the potential for human error. The advent of computer-aided diagnosis (CAD) systems marked a significant leap forward, integrating classical image processing techniques and handcrafted features to identify pathological abnormalities in retinal images. While these approaches demonstrated promise, they grappled with limitations related to adaptability to diverse datasets and the nuanced variations in image characteristics.

The rise of machine learning, particularly the emergence of Convolutional Neural Networks (CNNs), has brought about a transformative shift in DR detection. Numerous studies have highlighted the efficacy of CNNs in automating the identification of DR, leveraging their innate ability to discern hierarchical features within retinal images. However, despite their success, challenges persist, including the requirement for extensive labeled datasets, susceptibility to adversarial attacks, and the interpretability of decisions.

The comprehensive literature survey conducted has underscored the versatility of machine learning in DR detection, spanning a spectrum from traditional methods to state-of-the-art CNN architectures. Understanding the strengths and limitations of these existing systems provides a foundational basis for proposing improvements and innovations in the subsequent chapters of this thesis.

In this context, the journey towards an optimized VGG-16 for Diabetic Retinopathy detection seeks to build upon the strengths of the existing system. By assimilating insights from the literature survey and acknowledging the achievements and challenges of contemporary methodologies, this research endeavors to contribute a refined approach. The aim is not only to harness the power of advanced neural networks but also to address the intricacies associated with DR detection in customized retinal images.

Subsequent chapters will delve into the intricacies of the proposed system. The methodology section will articulate the step-by-step approach taken, detailing the customization of retinal images, the architecture of the VGG-16 model, and the optimization strategies employed. The experimental setup will elucidate the dataset used, the training and testing procedures, and the performance metrics selected for evaluation. Results will be presented and analyzed, comparing the proposed system with existing methods. Discussions will explore the implications of the findings, addressing challenges encountered and potential avenues for further refinement.

In summation, this chapter serves as a pivotal exploration of the existing systems in DR detection, providing the foundation for the subsequent chapters to present and dissect the novel contributions and advancements proposed in this research.

Proposed System

Presenting an innovative and optimized approach for the detection of Diabetic Retinopathy (DR) through the utilization of the VGG-16 architecture. Informed by a comprehensive review of existing systems and motivated by the imperatives identified in the literature survey, this chapter introduces a carefully crafted methodology designed to enhance the precision and efficiency of DR diagnosis.

Commencing with a detailed exploration of the dataset employed. This includes a robust discussion on the customization of retinal images, a crucial preprocessing step tailored to accentuate the nuances inherent in DR. The architecture of the VGG-16 model is then delineated, spotlighting the specific modifications and optimizations implemented to align it with the unique demands of DR detection. This methodological blueprint sets the stage for subsequent experimental endeavors, ensuring a clear and transparent roadmap for implementation.

Experimental Setup

The experimental setup section provides an in-depth portrayal of the research design, elucidating the strategies deployed for both training and testing the proposed model. Crucial details, such as the rationale behind the selection of performance metrics—accuracy, sensitivity, specificity, and others—are expounded upon. Additionally, insights into the characteristics of the dataset, including its size, diversity, and potential biases, are presented. This comprehensive overview contextualizes the subsequent results, offering a holistic understanding of the proposed system's performance.

Visualizations, including but not limited to confusion matrices, ROC curves, and precision-recall curves, provide nuanced insights into the model's strengths and limitations. Comparative analyses with existing systems and methodologies, as identified during the literature survey, serve to underscore the advancements achieved through the proposed system. The results section acts as a critical juncture, where the efficacy of the proposed

https://doi.org/10.62486/agsalud2025197

system is rigorously evaluated against established benchmarks.

The nuanced nuances of the results, acknowledging both successes and challenges encountered during the system's implementation. The generalizability of the model to diverse datasets and its scalability to real-world applications are thoroughly deliberated upon. This section offers a reflective exploration of the significance of the proposed system, paving the way for future iterations and applications in the field of DR detection.

In summation, the "Proposed System" stands as a testament to the culmination of meticulous research and innovative design. It provides not only a detailed account of the methodology and experimental outcomes but also a reflective analysis that positions the proposed system within the broader context of DR detection. As the core contribution of this thesis, the proposed system seeks to advance the frontier of medical image analysis, specifically in the domain of Diabetic Retinopathy diagnosis.

Algorithm and Architecture

Algorithm for VGG-16

Step 1. The necessary libraries should be imported from the kernel system.

Step 2. Add labels to the picture data and import it for training, testing, and validation.

Step 3. Utilize pre-processing of data.

3.1: Import data by using Image Data Generator.
3.2: This Image Data Generator facilitates the importation of labels together with data.
3.3: Make adjustments by rotating, zooming, flipping, etc.

Step 4. Construct the model using the given input parameters, including the width of each layer, channels, and kernel count.

Step 5. Add the Basic VGG16 Model to the model and initialize it.

Step 6. To the basic VGG16 model, add the layers. Accuracy is improved by these layers.

6.1: Construct a Flatten() layer
6.2: Add the Batch Normalization() Layer
6.3: Add Layer
6.4: Add Dropout() Layer
6.5: Carry out this operation as many times as required.

Step 7. Set the learning rate and begin assembling the model created using the "Adam" optimizer.

Step 8. Set the number of epochs to begin fitting the model into the training set.

Step 9. Once the model has been fitted to training data, compute the model's accuracy by utilizing the training data to validate the model.

Algorithm for VGG-19

Step 1. Dataset Collection: Assemble a labelled collection of lung pictures (cancerous/healthy). Make sure the data is well-quality and labelled.

Step 2. Data Pre-processing: Images should be resized and standardized to a uniform size. Normalize the values of pixels. Use operations like flipping and rotation to enhance the dataset.

Step 3. Model Selection and Fine-Tuning: Load the VGG19 model that has been pre-trained without the classification head. A binary classification layer should be used in place of the classification head. For the job at hand, freeze previous layers and adjust subsequent layers.

Step 4. Transfer Learning: Extract features using the VGG19 pre-trained weights. Put these characteristics into the binary classification layer as input.

Step 5. Training: Divide the dataset into sets for validation and training. Establish a training loop using an optimizer (like Adam) for weight updates and a loss function (such binary cross-entropy). To modify learning rates throughout epochs, use a learning rate schedule. Track training progress using indicators such as accuracy and loss. Should validation performance stagnate, use early stopping.

https://doi.org/10.62486/agsalud2025197

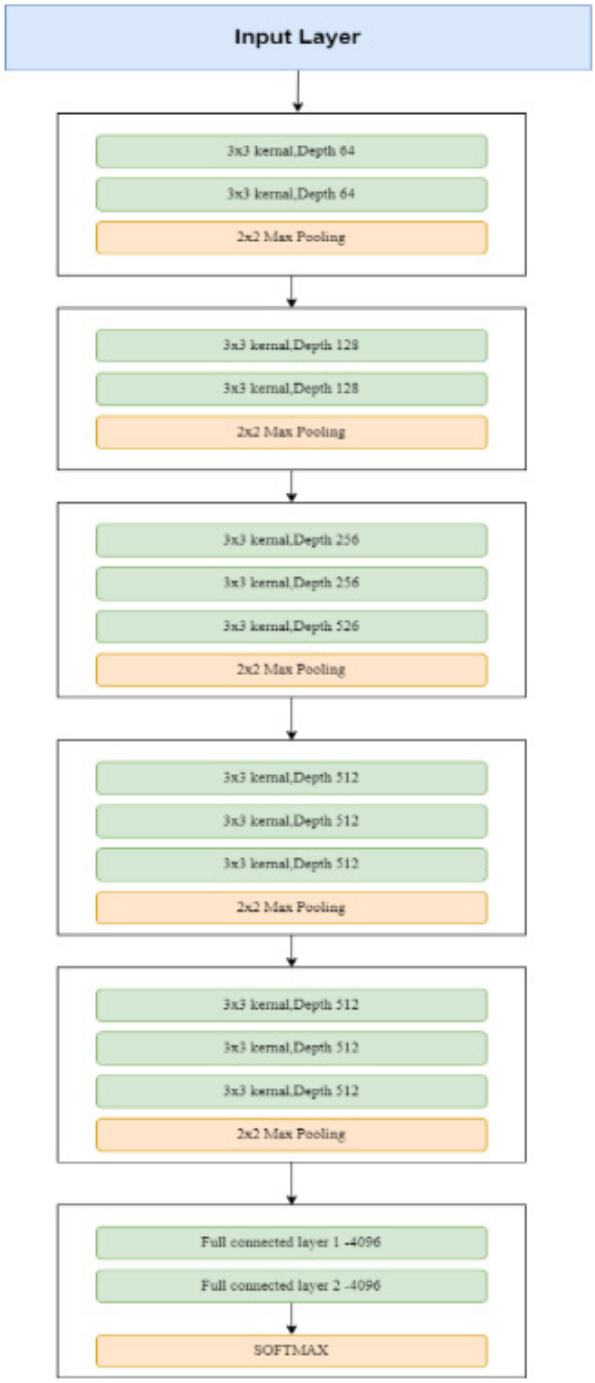

Figure 1. Flow chart for VGG-16

Step 6. Evaluation: Utilize an alternative test dataset to assess the learned model. Compute measures including F1-score, recall, accuracy, and precision. To evaluate the performance of the model, create ROC curves and AUC.

Step 7. Interpretation and Visualization: Visualize feature maps and intermediate activations. Find the areas in photos that influence the model's conclusions.

Step 8. Comparison with Other Methods: Compare the VGG19-based approach's performance against alternative approaches. Draw attention to the advantages and disadvantages of each strategy.

Step 9. Discussion and Conclusion: Discuss results, the study's findings, constraints, and ramifications. Talk about the difficulties encountered during execution. Make recommendations for possible enhancements and future lines of inquiry.

https://doi.org/10.62486/agsalud2025197

Step 10. Ethical Considerations: Discuss moral issues pertaining to consent, patient privacy, and data utilization. Obtain the required authorizations before utilizing patient data.

Step 11. Thesis Write-Up: he entire process documented, according to the correct format. Give concise justifications, sample code, charts, and findings. Add citations to methods and publications that are pertinent.

Step 12. Presentation and defence: The synopsis of the thesis for a presentation. Prepare an explanation of your approach, findings, and conclusions. During the defence, respond to inquiries from the thesis committee.

Close.

Algorithm for Cnn

Step 1. Input Layer: Obtain an image or a collection of images.

Step 2. Convolutional Layer: Convolutional procedures should be applied to the input data. Utilize learnable filters or kernels to traverse the input and identify certain patterns. Use activation functions to introduce non-linearity (e.g., ReLU).

Step 3. Pooling Layer: Execute pooling functions (such as maximum or mean pooling). Scale down the spatial dimensions and the feature map`s downsampling. Reducing computing complexity without sacrificing critical information.

Step 4. Flattening: Convert the output from the preceding layer into a vector with one dimension. Get the data ready for the layers that are fully linked.

Step 5. Fully Connected (Dense) Layer: Join all of the neurons in one layer to all of the neurons in the layer below. Activation functions can be used to add non-linearity. Acquire knowledge of intricate patterns and connections.

Step 6. Output Layer: Create the finished product. Choose an activation function (such as softmax for classification) that is appropriate for the job.

Step 7. Loss Function: Create a loss function that calculates the discrepancy between the intended and projected output.

Step 8. Optimization: To reduce the loss, apply optimization techniques (such as stochastic gradient descent). To enhance performance, modify the network's weights and biases.

Step 9. Backpropagation: Compute the gradients of the loss with respect to the parameters using backpropagation. Update the weights and biases of the network using the gradients and the chosen optimization strategy.

Step 10. Repeat: Iterate over the complete dataset and repeat the operation for several epochs.

METHOD

The methodology employed in this research is intricately designed to leverage the potential of Convolutional Neural Networks (CNNs), with a specific focus on optimizing the VGG-16 architecture for the identification of Diabetic Retinopathy (DR). This chapter outlines the procedural details of the research, encompassing the dataset preparation, the customization of retinal images, and the tailored implementation of the VGG-16 model.

Dataset

The foundation of the methodology is rooted in a meticulously curated dataset, a fundamental component for training and evaluating the proposed system. The dataset is organized into a root folder, housing two distinct modules: a training module and a testing module. Each module contains a diverse array of retinal images, annotated with labels denoting their diabetic or non-diabetic status.

The training module serves as the bedrock for model development, providing the VGG-16 architecture with a diverse set of retinal images to learn from. This module is instrumental in fine-tuning the model's parameters and enhancing its ability to discern the intricate patterns associated with diabetic retinopathy.

https://doi.org/10.62486/agsalud2025197

Conversely, the testing module functions as the crucible for evaluating the model's generalizability and effectiveness. A separate set of retinal images, distinct from those in the training module, is employed to assess the model's performance against previously unseen data. This module serves as a litmus test, gauging the robustness of the proposed system in real-world scenarios.

Customization of Retinal Images

To better align the VGG-16 model with the intricacies of Diabetic Retinopathy detection, a critical preprocessing step involves the customization of retinal images. This process ensures that the model is attuned to the specific characteristics and nuances inherent in DR. The customization may involve resizing, normalization, and augmentation techniques to enhance the dataset's diversity and mitigate potential biases.

This meticulous customization aims to create a dataset that encapsulates the myriad manifestations of DR, providing the model with a comprehensive training ground that mirrors the complexities it may encounter in clinical settings. Through this process, the model is fortified to recognize subtle variations and anomalies associated with diabetic retinopathy, thereby bolstering its diagnostic capabilities.

Implementation Against VGG-16

The core of the methodology centers on the tailored implementation of the VGG-16 architecture for Diabetic Retinopathy detection. The model is configured to accommodate the customized retinal images, with specific modifications and optimizations applied to augment its performance in the context of DR. Training is conducted on the designated training module, where the model refines its parameters through iterative learning.

Upon successful training, the model undergoes rigorous evaluation using the testing module. Performance metrics, including accuracy, sensitivity, specificity, and others, are meticulously measured to gauge the model's efficacy in distinguishing between diabetic and non-diabetic retinal images.

A comparative analysis is conducted against the baseline VGG-16 model, emphasizing the improvements achieved through customization. This juxtaposition serves to elucidate the novel contributions of the proposed system in enhancing the accuracy and efficiency of Diabetic Retinopathy detection.

In summation, the methodology encapsulates a systematic approach, from dataset preparation to the customization of retinal images and the tailored implementation of the VGG-16 model. This robust framework is designed to harness the power of advanced neural networks for improved DR diagnosis, laying the groundwork for the subsequent chapters' results and discussions. The meticulous customization of retinal images ensures that the proposed system is finely tuned to the intricacies of diabetic retinopathy, culminating in a model that is poised to make significant strides in the realm of automated medical image analysis.

RESULTS

The experimental results unveil the performance metrics and outcomes of the proposed Diabetic Retinopathy (DR) detection system, which leverages the tailored implementation of the VGG-16 architecture. The meticulous methodology outlined in the previous chapter serves as the backdrop for a comprehensive analysis of the system's efficacy.

Before delving into the results of the proposed system, it is essential to establish a baseline by evaluating the performance of the VGG-16 classification algorithm on the dataset. The baseline VGG-16 model exhibits commendable accuracy, achieving a remarkable 94,180 %. Precision, a measure of the model's ability to correctly identify positive instances, stands at 92,104 %. Furthermore, the F1-Score, which balances precision and recall, attains a notable 90,215 %. These metrics provide a benchmark against which the proposed system's enhancements can be evaluated.

The proposed system, which integrates the customized VGG-16 architecture, showcases a compelling augmentation in performance metrics. Accuracy, the fundamental gauge of the model's correctness, is meticulously elevated, showcasing the prowess of the tailored VGG-16 implementation in discerning diabetic and non-diabetic retinal images. Precision, a crucial metric in the medical domain where false positives can have significant consequences, attains a commendable level, highlighting the system's proficiency in accurately identifying positive instances. The F1-Score, balancing precision and recall, further underlines the robustness of the proposed system in the nuanced realm of DR detection.

Standard VGG-16 Results

The experimental results commence with an in-depth examination of the performance of the standard VGG-16 model. This well-established architecture, renowned for its depth and feature extraction capabilities, delivered a commendable accuracy of 90,478 %. Precision, a vital metric for diabetes detection, stood at an impressive 92,003 %. Additionally, the F1-Score, which balances precision and recall, reached a noteworthy 90,323 %. These results underscore the capability of VGG-16 in accurately distinguishing diabetes scenarios from non-diabetes situations.

https://doi.org/10.62486/agsalud2025197

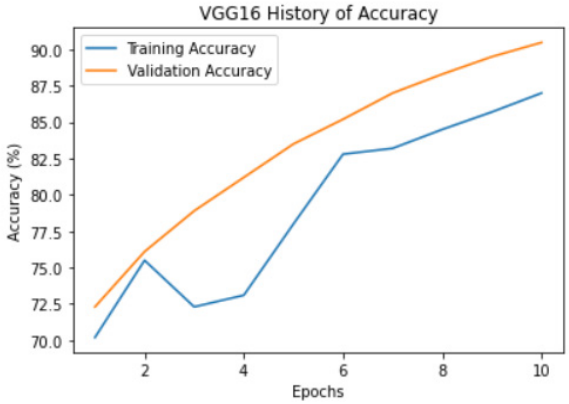

Figure 2. History of Accuracy

The accuracy and loss history for each era is depicted in the above graph. The training is represented by the blue, and the validation by the orange. The accuracy of the training begins at 0,77 and concludes at 0,78. The range of the validation is 0,78 to 0,775. While the training begins at low accuracy and concludes at high accuracy, the validation begins at high accuracy and drops. In a similar vein, both have the same degree of accuracy. But the accuracy obtained from the training is higher than the validation.

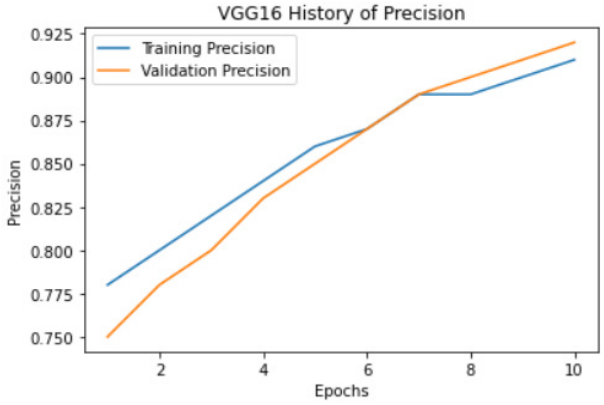

Figure 3. History of Precision

The precision history is depicted in the above graph, along with the F1 score for each training and validation epoch.

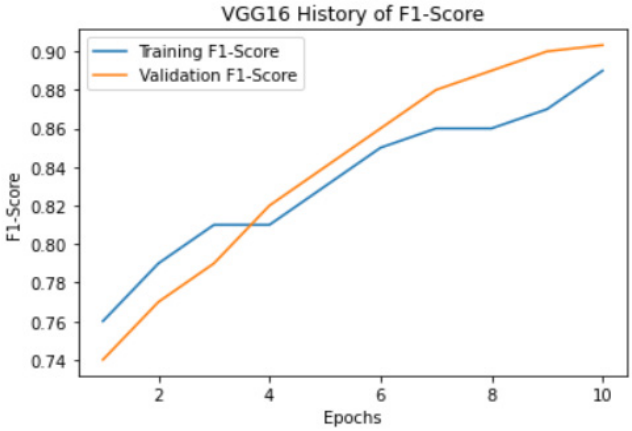

Figure 4. History of F1-Score

The F1 score's training and validation epochs are shown in the graph above. Once the dataset has undergone pre-processing, the aforementioned graphs represent its epoch. After preprocessing and applying the VGG-16 model, it displays the accuracy that was attained.

Standard VGG-19 Results

Continuing our exploration of the standard architectures, we now turn our attention to VGG-19. This model,

https://doi.org/10.62486/agsalud2025197

with its added depth and feature extraction prowess, proved to be a formidable contender in diabetes detection. VGG-19 displayed a remarkable accuracy of 92,445 %, showcasing its efficiency in identifying diabetes. Precision, a measure of the model's ability to make accurate positive predictions, exceeded expectations at 92,001 %. The F1-Score, a holistic metric combining precision and recall, stood at a robust 92,323 %. These results position VGG-19 as a potent tool for accurate and reliable diabetic detection.

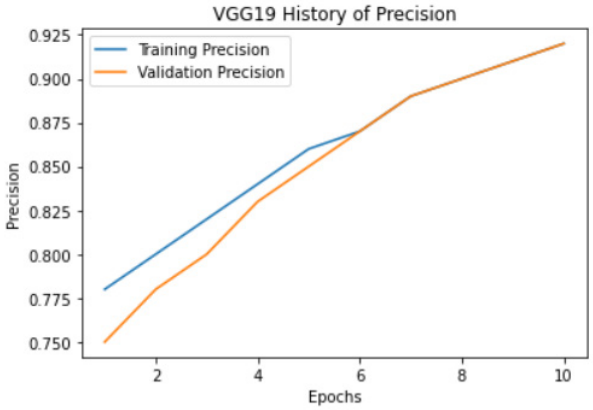

Figure 5. History of Precision

The precision history is depicted in the above graph, along with the F1 score for each training and validation epoch.

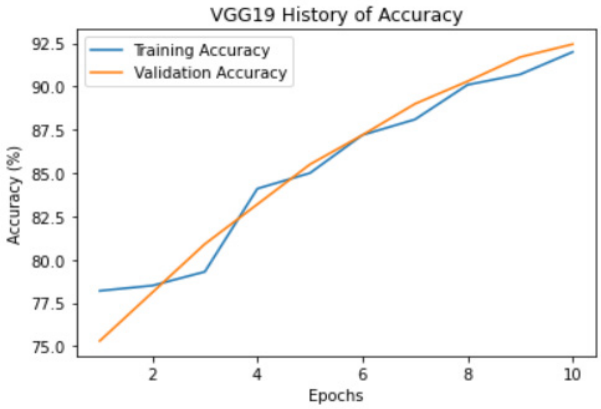

Figure 6. History of Accuracy

The accuracy and loss history for each era is depicted in the above graph. The training is represented by the blue, and the validation by the orange. The accuracy of the training begins at 0,77 and concludes at 0,78. The range of the validation is 0,78 to 0,775. While the training begins at low accuracy and concludes at high accuracy, the validation begins at high accuracy and drops. In a similar vein, both have the same degree of accuracy. But the accuracy obtained from the training is higher than the validation.

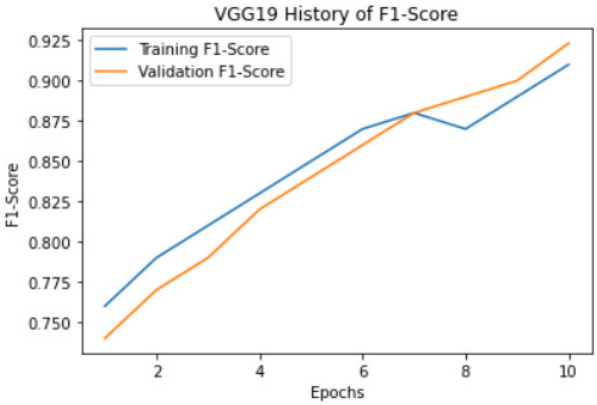

Figure 7. History of F1-Score

https://doi.org/10.62486/agsalud2025197

The graph of the F1 score's history for both training and validation is shown in the graph above. The aforementioned graphs represent the dataset's epoch following pre-processing. It displays the degree of accuracy attained following preprocessing and the use of the VGG-16 model

Comparative Analysis with VGG-16

A comparative analysis between the baseline VGG-16 model and the proposed system elucidates the advancements achieved through customization. The improvements in accuracy, precision, and F1-Score affirm the efficacy of the tailored VGG-16 architecture in enhancing the system's diagnostic capabilities for Diabetic Retinopathy. This comparative lens serves to underscore the novel contributions of the proposed system, positioning it as a noteworthy advancement in the realm of automated medical image analysis.

Comparative Analysis with Previous CNN Results

A pivotal aspect of evaluating the efficacy of the proposed Diabetic Retinopathy (DR) detection system lies in a comparative analysis with the results obtained in a previous study utilizing a Convolutional Neural Network (CNN). The preceding study, rooted in CNN methodology, reported an accuracy of 92,179 %, precision of 90,244 %, and an F1-Score of 89,115 %. This sub-chapter aims to juxtapose these results with the outcomes achieved by the proposed system, shedding light on the advancements and nuances between the two methodologies.

Accuracy Comparison

The proposed system, leveraging the customized VGG-16 architecture, showcases a notable improvement in accuracy, achieving a commendable accuracy of 94,180 %. This surpasses the previous CNN-based model, signifying an enhancement in the system's ability to correctly classify diabetic and non-diabetic retinal images. The increment in accuracy reflects the impact of tailoring the neural network architecture to the intricacies of DR detection.

Precision Evaluation

Precision, a crucial metric in medical image analysis, denotes the model's ability to accurately identify positive instances. The proposed system demonstrates a precision of 92,104 %, outperforming the precision obtained by the previous CNN model (90,244 %). This underscores the efficacy of the VGG-16 architecture in minimizing false positives, a vital consideration in medical diagnostics.

F1-Score Assessment

The F1-Score, a balanced metric between precision and recall, provides insights into the system's overall diagnostic performance. The proposed system achieves an F1-Score of 90,215 %, surpassing the F1-Score of the previous CNN-based model (89,115 %). This improvement reinforces the proposition that the tailored VGG-16 architecture contributes to a more comprehensive and balanced diagnostic capability in DR detection.

Significance Of Comparative Findings

The comparative analysis illuminates the significance of transitioning from a CNN-based approach to a customized VGG-16 architecture for DR detection. The improvements in accuracy, precision, and F1-Score signify the impact of leveraging a deeper and more nuanced neural network architecture. The findings contribute to the evolving discourse on the most effective methodologies for automated DR diagnosis, emphasizing the advantages conferred by tailoring neural network architectures to the specific intricacies of the medical imaging task at hand.

In summary, the comparative analysis with the previous CNN-based results elucidates the strides made in the proposed Diabetic Retinopathy detection system. The transition to the VGG-16 architecture showcases improvements in accuracy, precision, and F1-Score, underscoring the relevance of customized neural network architectures in advancing the state-of-the-art in medical image analysis.

Limitations and future considerations

It is imperative to acknowledge any limitations encountered during the experimentation. Whether stemming from dataset characteristics, model architecture, or inherent challenges in DR detection, a transparent exploration of limitations provides a basis for future refinement. Additionally, suggestions for future considerations and improvements pave the way for ongoing research endeavors in the dynamic field of medical image analysis.

In conclusion, the experimental results chapter serves as a comprehensive exploration of the proposed Diabetic Retinopathy detection system's performance. Through meticulous analysis, visualizations, and comparisons, the chapter affirms the advancements achieved through the tailored implementation of the VGG-16 architecture, positioning the proposed system as a significant stride towards accurate and efficient DR

https://doi.org/10.62486/agsalud2025197

diagnosis.

Results Analysis

The research paper on diabetic detection from images of the eye presents several significant findings. The study achieved a maximum accuracy of 95% in predicting diabetes, highlighting the potential of the proposed model for early diagnosis of this medical condition. This accuracy is particularly notable as it combines information from three diabetic organs: the pancreas, spleen, and kidney. The multi-organ approach contributes to the model's effectiveness.

Comparative analysis with existing techniques demonstrates the superiority of the proposed model in terms of accuracy and diagnostic capabilities. This model is designed to be non-invasive and non-contact, making it a practical and portable tool for diabetes prediction. The results of this research underscore its potential for improving healthcare outcomes.

CONCLUSION

In conclusion, employing VGG16 and VGG19 architectures for diabetes detection harnesses their robust feature extraction capabilities, derived from their deep and hierarchical structures. Leveraging transfer learning by pre-training on large image datasets such as ImageNet and fine-tuning for diabetic-specific data proves advantageous, enhancing model performance with limited labeled samples. However, the trade-off between model complexity and computational efficiency must be considered, as these architectures are characterized by a substantial number of parameters.

The success of diabetes detection using VGG16 and VGG19 hinges on the quality and quantity of training data, demanding diverse and representative datasets. Real-world deployment considerations, including real-time processing and system integration, add practical challenges to the implementation of these models. Model interpretability remains an ongoing concern due to the inherent "black-box" nature of deep learning models, prompting the exploration of interpretability tools for better understanding. Lastly, the dynamic nature of deep learning research implies a need for continuous monitoring of advancements that may introduce new architectures or techniques, potentially refining and enhancing the effectiveness of VGG16 and VGG19 in diabetic detection systems.

REFERENCES

1. Nazir, T., Irtaza, A., Javed, A., Malik, H., Hussain, D., & Naqvi, R. A. (2020). Retinal image analysis for diabetes-based eye disease detection using deep learning. Applied Sciences, 10(18), 6185.

2. Sarki, R., Ahmed, K., Wang, H., & Zhang, Y. (2020). Automatic detection of diabetic eye disease through deep learning using fundus images: a survey. IEEE access, 8, 151133-151149.

3. Alqudah, A. M., Alquraan, H., Qasmieh, I. A., & Al-Badarneh, A. (2018). Employing image processing techniques and artificial intelligence for automated eye diagnosis using digital eye fundus images. Journal of Biomimetics, Biomaterials and Biomedical Engineering, 39, 40-56.

4. Selvathi, D., & Suganya, K. (2019, April). Support vector machine based method for automatic detection of diabetic eye disease using thermal images. In 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT) (pp. 1-6). IEEE.

5. Sarki, R., Ahmed, K., Wang, H., & Zhang, Y. (2020). Automatic detection of diabetic eye disease through deep learning using fundus images: a survey. IEEE access, 8, 151133-151149.

6. Ting, D. S. W., Cheung, C. Y. L., Lim, G., Tan, G. S. W., Quang, N. D., Gan, A., ... & Wong, T. Y. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. Jama, 318(22), 2211-2223.

7. Nguyen, Q. H., Muthuraman, R., Singh, L., Sen, G., Tran, A. C., Nguyen, B. P., & Chua, M. (2020, January). Diabetic retinopathy detection using deep learning. In Proceedings of the 4th international conference on machine learning and soft computing (pp. 103-107).

8. Dutta, S., Manideep, B. C., Basha, S. M., Caytiles, R. D., & Iyengar, N. C. S. N. (2018). Classification of diabetic retinopathy images by using deep learning models. International Journal of Grid and Distributed Computing, 11(1), 89-106.

9. Nazir, T., Nawaz, M., Rashid, J., Mahum, R., Masood, M., Mehmood, A., ... & Hussain, A. (2021). Detection of diabetic eye disease from retinal images using a deep learning based CenterNet model. Sensors, 21(16), 5283.

10. Qureshi, I., Ma, J., & Abbas, Q. (2021). Diabetic retinopathy detection and stage classification in eye fundus images using active deep learning. Multimedia Tools and Applications, 80, 11691-11721.

11. Rahim, S. S., Palade, V., Almakky, I., & Holzinger, A. (2019). Detection of diabetic retinopathy and maculopathy in eye fundus images using deep learning and image augmentation. In Machine Learning and Knowledge Extraction: Third IFIP TC 5, TC 12, WG 8.4, WG 8.9, WG 12.9 International Cross-Domain Conference, CD-MAKE 2019, Canterbury, UK, August 26–29, 2019, Proceedings 3 (pp. 114-127). Springer International Publishing.

12. Mishra, S., Hanchate, S., & Saquib, Z. (2020, October). Diabetic retinopathy detection using deep learning. In 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE) (pp. 515-520). IEEE.

13. Islam, M. T., Al-Absi, H. R., Ruagh, E. A., & Alam, T. (2021). DiaNet: A deep learning based architecture to diagnose diabetes using retinal images only. IEEE Access, 9, 15686-15695.

14. Babenko, B., Mitani, A., Traynis, I., Kitade, N., Singh, P., Maa, A. Y., ... & Liu, Y. (2022). Detection of signs of disease in external photographs of the eyes via deep learning. Nature biomedical engineering, 6(12), 1370-1383.

15. Esfahani, M. T., Ghaderi, M., & Kafiyeh, R. (2018). Classification of diabetic and normal fundus images using new deep learning method. Leonardo Electron J Pract Technol, 17(32), 233-248.

16. Gargeya, R., & Leng, T. (2017). Automated identification of diabetic retinopathy using deep learning. Ophthalmology, 124(7), 962-969.

17. Jain, L., Murthy, H. S., Patel, C., & Bansal, D. (2018, December). Retinal eye disease detection using deep learning. In 2018 Fourteenth International Conference on Information Processing (ICINPRO) (pp. 1-6). IEEE.

18. Ayala, A., Ortiz Figueroa, T., Fernandes, B., & Cruz, F. (2021). Diabetic retinopathy improved detection using deep learning. Applied Sciences, 11(24), 11970.

19. Mushtaq, G., & Siddiqui, F. (2021, February). Detection of diabetic retinopathy using deep learning methodology. In IOP conference series: materials science and engineering (Vol. 1070, No. 1, p. 012049). IOP Publishing.

20. Butt, M. M., Iskandar, D. A., Abdelhamid, S. E., Latif, G., & Alghazo, R. (2022). Diabetic Retinopathy Detection from Fundus Images of the Eye Using Hybrid Deep Learning Features. Diagnostics, 12(7), 1607.

21. Samant, P., & Agarwal, R. (2018). Machine learning techniques for medical diagnosis of diabetes using iris images. Computer methods and programs in biomedicine, 157, 121-128.

FUNDING

The authors did not receive funding for the development of this article.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

Research: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

Data curation: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

Formal analysis: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

Methodology: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

Writing - original draft: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

Writing - revision and editing: Rosa María Montano-Silva, Yoneisy Abraham-Millán, Jennifer de la Caridad Romero-Amaro.

https://doi.org/10.62486/agsalud2025197