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RetinaGuard AI: Harnessing SVM, KNN, and Deep Learning for Diabetic Retinopathy Diagnosis

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Abstract : This review examines recent advances in deep learning techniques for the detection and classification of Diabetic Retinopathy (DR) in retinal fundus images. Diabetes- related retinopathy, a leading cause of blindness in diabetics, needs to be detected early for effective treatment. Traditional manual diagnosis methods are time-consuming and prone to errors. To assess the effectiveness of various deep learning models, such as CNNs, VGG-16, VGG-19, and Vision Transformers, we employ a wide range of deep learning models, including CNNs, VGG-16, VGG-19, and Vision Transformers. As part of the review, available data for DR- related fundus images are surveyed, and research gaps and challenges are identified. Researchers, clinicians, and stakeholders interested in improving the effectiveness of automated systems for the early diagnosis and management of Diabetic Retinopathy will find this review to be a valuable resource because it synthesises current knowledge and highlights areas for future exploration.

***IndexTerms* - Diabetic Retinopathy, deep learning, retinal fundus images, CNNs, VGG-16, VGG-19, Classification**

I. INTRODUCTION

Diabetic retinopathy (DR) can cause blindness in individuals with diabetes due to its progressive damage to the retina. There are several stages of diabetic retinopathy, from mild Non proliferative retinopathy to advanced proliferative retinopathy, each with its manifestations. The importance of early detection cannot be overstated, as advanced stages can cause irreversible vision loss. Worldwide, DR is a leading cause of blindness, affecting 2.6% of cases. The risk escalates for those with long- standing diabetes.

The complexity of DR diagnosis lies in the variety of lesions on the retina, including microaneurysms (MA), hemorrhages (HM), and soft and hard exudates (EX). Developing an automatic detection solution becomes imperative, considering the challenges in accurately identifying and assessing these lesions. Regular retinal screening is vital for timely diagnosis and intervention, emphasising the need for efficient and reliable automated methods.

These papers explore the evolution of automated DR detection methods, addressing manual diagnosis limitations, such as the propensity for misdiagnosis and the significant time and effort required. The stages of DR, classified based on lesion presence, further highlight the necessity for precise and swift detection methods. Leveraging technological advancements, the review delves into the characteristics of lesions and the stages of DR, offering insights into the potential of automated solutions for revolutionising the diagnostic landscape. By evaluating existing methodologies and advancements, this review aims to provide a comprehensive understanding of automated DR detection's current state and prospects, contributing to enhanced patient care and vision preservation.

To address these challenges, there has been a growing emphasis on the development and implementation of automated solutions for DR detection. The integration of technology, particularly deep learning and image analysis techniques has paved the way for efficient and reliable diagnostic tools. Automated methods not only streamline the diagnosis process but also offer a more objective and consistent approach, mitigating the risks associated with manual diagnosis, such as subjectivity and human error.

This review delves into the intricacies of DR detection, emphasising the significance of early intervention to prevent irreversible vision loss. By exploring the characteristics of various lesions, including microaneurysms, hemorrhages, and exudates, and their correlation with distinct DR stages, this paper aims to shed light on the potential of automated systems in revolutionising the detection and classification of DR. Furthermore, it assesses the advantages of automated methods, such as cost and time efficiency, and examines the evolving landscape of DR diagnosis in the era of technological innovation. Ultimately, this review seeks to contribute to the ongoing discourse on improving patient outcomes through advanced and accessible diagnostic solutions for diabetic retinopathy.

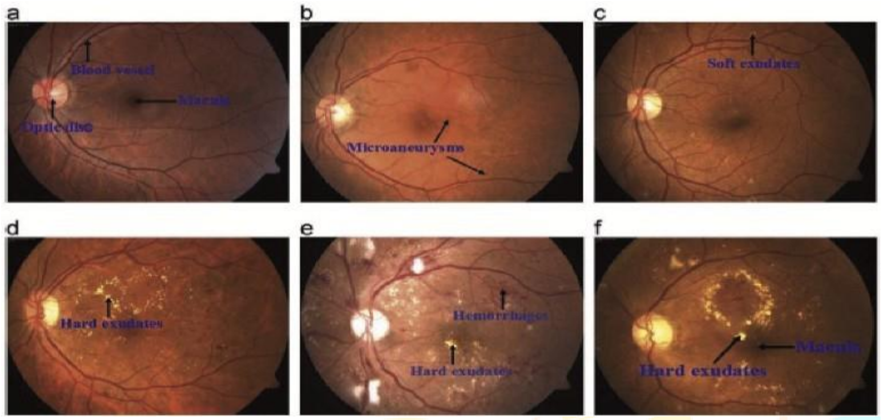

Fig. 1. The DR stages: (a) normal retinal (b) Mild DR, (c) Moderate DR, (d) Severe DR, (e) Proliferative DR,(f) Macular edema

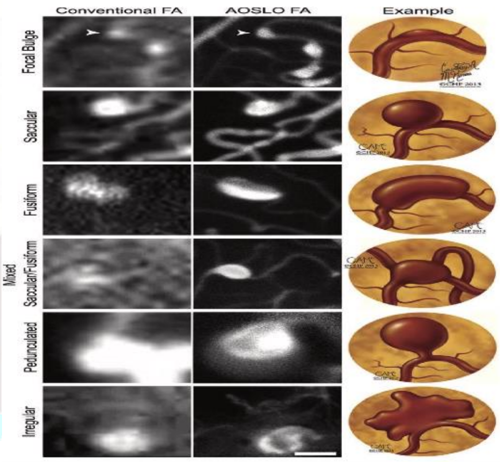

Fig. 2. The Different types of MA

1.1 Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) are a pivotal innovation in deep learning, particularly adept at processing visual data. Designed with convolutional layers, CNNs excel in recognising hierarchical features crucial for tasks like image classification and object detection. Their ability to automatically learn complex patterns has made them indispensable in various applications, from facial recognition to medical image analysis. In the realm of diabetic retinopathy detection, CNNs play a crucial role, providing a robust framework for automated analysis of retinal fundus images.

1.2 Deep Learning (DL):

Deep learning represents a transformative paradigm in artificial intelligence, characterised by intricate neural network architectures capable of learning intricate representations from vast datasets. At its core, deep learning mimics the human brain's neural structure, allowing machines to autonomously discern and process complex patterns. The depth of these neural networks enables the automatic extraction of hierarchical features, making deep learning particularly potent in solving intricate problems like image recognition, natural language processing, and medical diagnosis.

1.3 Support Vector Machines (SVM):

Support Vector Machines (SVM) represent a powerful and versatile class of supervised machine learning algorithms with applications spanning classification and regression tasks. SVM excels in finding optimal hyperplanes that effectively separate data points into distinct classes, making it particularly well-suited for binary classification challenges. Its strength lies in maximising the margin between different classes, promoting robust generalisation to new data. SVM's adaptability extends to non-linear datasets through the use of kernel functions, allowing it to capture intricate relationships and patterns. Renowned for its efficiency in high- dimensional spaces, SVM continues to be a valuable tool in various domains, including image classification, text categorisation, and bioinformatics.

1.4 K-Nearest Neighbors (KNN):

K-Nearest Neighbors (KNN) is a simple yet powerful algorithm in machine learning, classified under the umbrella of supervised learning. This algorithm operates on the principle of proximity, where it classifies a data point based on the majority class of its k-nearest neighbors. In other words, KNN makes predictions by considering the characteristics of its closest data points, making it particularly effective for tasks like classification and regression. Its simplicity and intuitive approach make KNN a popular choice, especially in scenarios where the underlying patterns in the data are not explicitly defined, and the emphasis lies on leveraging the proximity of data points for accurate predictions.

1.5 Binary classification:

Binary classification serves as a fundamental approach in machine learning, simplifying complex decision-making into two distinct outcomes: positive or negative, presence or absence. In this paradigm, the objective is to classify instances into one of two exclusive categories, making it a straightforward and widely applied technique across various domains. Whether identifying spam emails, determining the likelihood of a medical condition, or predicting customer churn, binary classification provides a robust and interpretable framework for tasks where the end goal is a binary decision. Its simplicity and efficiency make it a cornerstone in the broader landscape of classification algorithms, offering valuable insights and actionable outcomes with a clear and concise decision boundary.

1.6 Multi-level classification:

Multi-level classification expands the scope of traditional binary classification by accommodating scenarios where instances can belong to multiple categories. In this nuanced approach, each instance is assigned to one or more classes from a set of possibilities, providing a more comprehensive understanding of complex relationships within the data. This versatile classification paradigm is instrumental in diverse fields such as natural language processing, image recognition, and medical diagnostics, where the inherent complexity of real-world scenarios demands a more granular categorisation. Multi-level classification algorithms enable a fine-grained analysis, empowering systems to capture the intricacies of diverse classes and facilitating more informed decision-making in situations where objects or phenomena may exhibit characteristics of multiple categories simultaneously.

1.7 Lesion-based classification:

Lesion-based classification delves into the realm of medical diagnostics, focusing on the identification and categorisation of specific pathological features or lesions within a given dataset. This approach is particularly crucial in fields like dermatology and ophthalmology, where accurate detection and classification of lesions can significantly impact diagnosis and treatment. By concentrating on the unique characteristics of lesions, such as shape, texture, and size, lesion-based classification algorithms play a pivotal role in automating the analysis of medical images. Whether discerning skin abnormalities or identifying lesions in retinal images for conditions like diabetic retinopathy, this targeted classification method contributes to the precision and efficiency of medical diagnostics, ultimately enhancing patient care.

1.8 Vessel-based classification:

Vessel-based classification constitutes a specialised approach in image analysis, honing in on the intricate network of blood vessels within a given dataset. This classification method is particularly vital in medical imaging, especially in areas like retinal analysis for conditions such as diabetic retinopathy. By scrutinising the distinct patterns and characteristics of blood vessels, vessel-based classification algorithms contribute to a more targeted understanding of vascular structures. This focused approach enhances the precision of diagnostics and facilitates the identification of abnormalities, ultimately aiding clinicians in making informed decisions regarding patient care. Vessel-based classification stands as an indispensable tool in medical image analysis, offering valuable insights into the intricate vasculature for improved diagnostic accuracy and treatment planning.

II. METHODOLOGY

Machine learning plays a crucial role in the early detection and screening of diabetic retinopathy, a condition affecting the eyes. By automatically analysing retinal images, machine learning algorithms contribute to precise predictions through a process known as feature extraction. Relevant features for identifying diabetic retinopathy include anomalies in blood vessels, microaneurysms, exudates, hemorrhages, and characteristics of the optic disc. These features can be automatically extracted from retinal images using machine learning approaches, such as convolutional neural networks (CNNs) or image processing algorithms.

CNNs, a type of deep learning architecture, excel in classifying images, making them well-suited for studying retinal images. They have proven highly effective in detecting diabetic retinopathy, often surpassing or matching human specialists. CNNs, such as the VGG16 architecture, are powerful tools for early diagnosis and screening, as they can automatically learn relevant features from raw images, potentially improving patient outcomes and reducing the workload for medical practitioners.

The VGG16 architecture, widely used in computer vision applications, including diabetic retinopathy identification, consists of 16 layers, including convolutional layers, pooling layers, and fully connected layers. Its deep architecture and transfer learning capabilities allow it to successfully learn complex features from retinal images, providing accurate and reliable diagnoses.

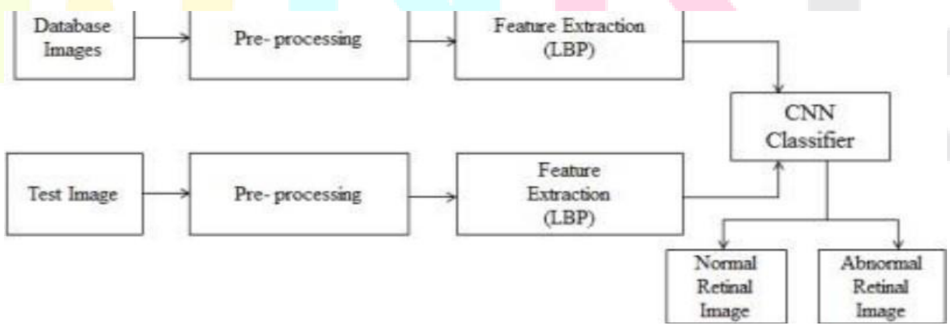

Fig. 3. Basic block diagram

After feature extraction, various machine learning techniques can be employed for categorisation tasks. Decision trees, K-nearest neighbors (KNN), XGBoost, AdaBoost, Voting Classifier, random forests, support vector machines (SVMs), logistic regression, and Naïve Bayes are common methods used in identifying diabetic retinopathy. These algorithms differentiate between retinal images with normal function and those depicting various stages or severity of diabetic retinopathy using labeled datasets.

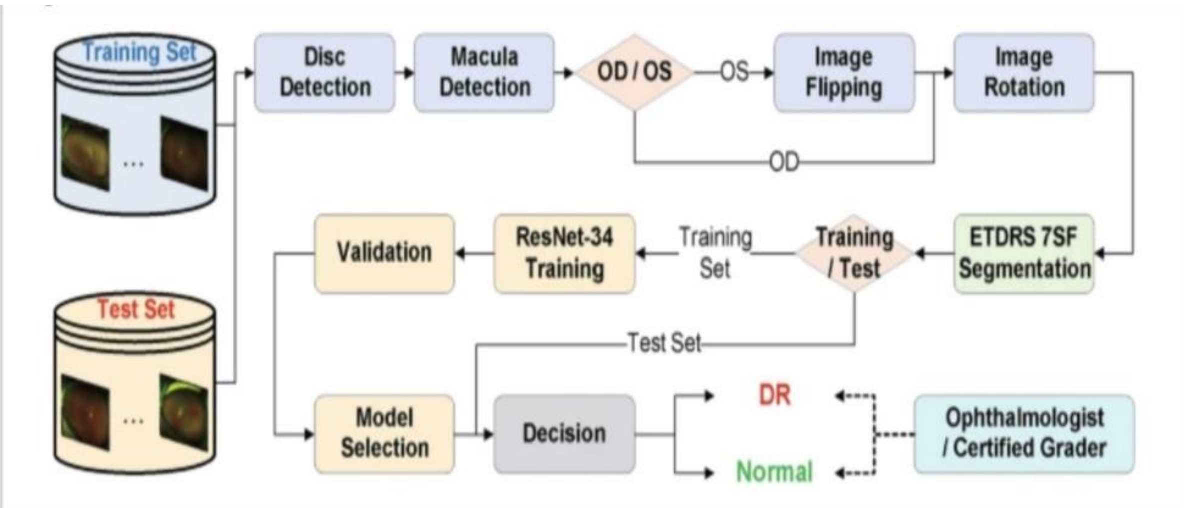

Fig. 4. Model flow diagram

Evaluation of a machine learning model's performance in detecting diabetic retinopathy involves metrics such as accuracy, precision, recall, and F1 score. These metrics provide information on how well the algorithm can identify diabetic retinopathy and accurately classify retinal images. Cross-validation techniques like k-fold cross-validation may be employed to obtain more reliable performance estimates. Overall, the integration of machine learning in the analysis of retinal images enhances the efficiency and accuracy of diabetic retinopathy detection, contributing to improved patient care.

III. RESULT

This process presents the detection results to the users or medical professionals. It provides a user interface to display the retinopathy level to the users.

The imaging technology allows healthcare professionals to detect subtle changes in the retina, which allows them to tailor treatment plans according to these subtle changes. Ultimately, the successful detection of diabetic retinopathy contributes to improved patient outcomes, ensuring that individuals with diabetes receive prompt and targeted care to preserve their vision and overall ocular health. Through its preservation of vision and mitigation of the risk of severe vision impairment or blindness, it improves overall patient outcomes. The reduction of long-term healthcare costs associated with advanced stages of diabetic retinopathy not only improves the quality of life for diabetics but also reduces the burden on healthcare systems.

The front-end of the project is Fig below. Where the image must be uploaded and the category in which the image falls is displayed as shown.

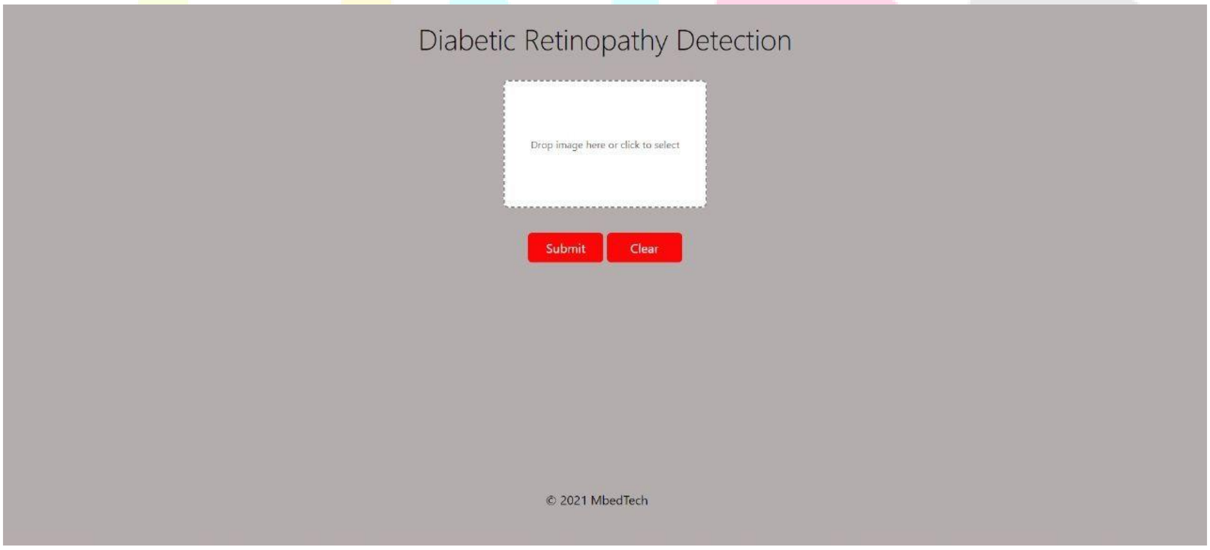

Fig. 5.1. Browser Interface

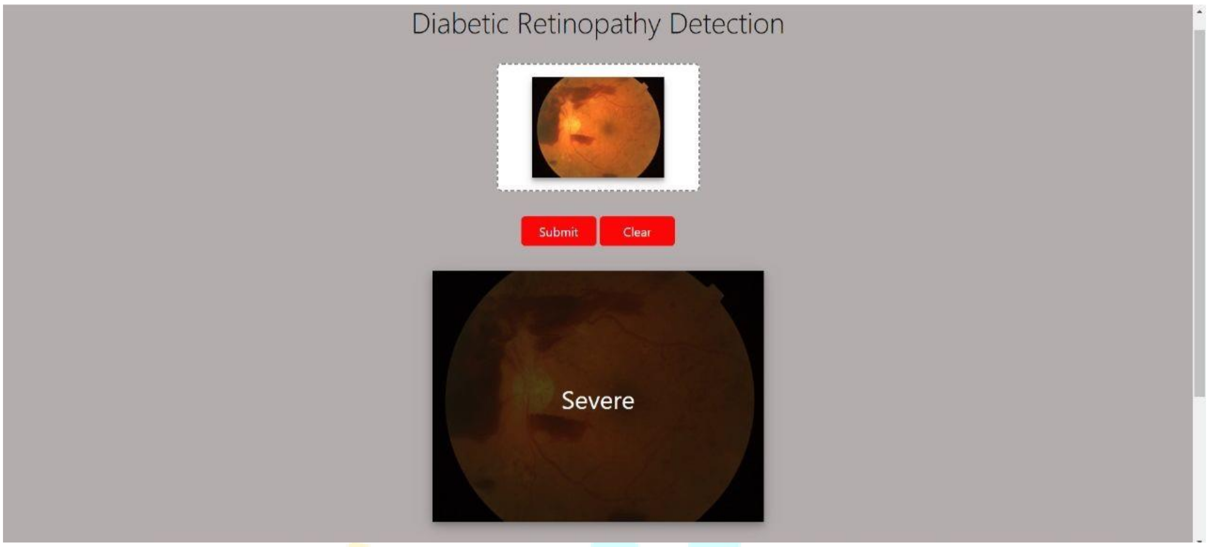

Fig. 5.2. Result

S.No	Test Scenario	Test Case	Predictions	Test Steps	Test Data	Expected Results	Post conditions	Actual Result	Status
1.	Detection of Severity level of Diabetic Retinopathy	Retinal Image captured through Fundus Idea	Trained CNN model	Retinal image capturing and sending it to build model	Dataset containing all the classes of Diabetic Retinopathy	Classifying the image into No_DR	Results are stored for further analyzes	Image is classified into No_DR	Pass
2.	Detection of Severity level of Diabetic Retinopathy	Retinal Image captured through Fundus Idea	Trained CNN model	Retinal image capturing and sending it to build model	Dataset containing all the classes of Diabetic Retinopathy	Classifying the image into Mild	Results are stored for further analyzes	Image is classified into Mild	Pass
3.	Detection of Severity level of Diabetic Retinopathy	Retinal Image captured through Fundus Idea	Trained CNN model	Retinal image capturing and sending it to build model	Dataset containing all the classes of Diabetic Retinopathy	Classifying the image into Moderate	Results are stored for further analyzes	Image is classified into Moderate	Pass
4.	Detection of Severity level of Diabetic Retinopathy	Retinal Image captured through Fundus Idea	Trained CNN model	Retinal image capturing and sending it to build model	Dataset containing all the classes of Diabetic Retinopathy	Classifying the image into Proliferate	Results are stored for further analyzes	Image is classified into Proliferate	Pass
5.	Detection of Severity level of Diabetic Retinopathy	Retinal Image captured through Fundus Idea	Trained CNN model	Retinal image capturing and sending it to build model	Dataset containing all the classes of Diabetic Retinopathy	Classifying the image into Severe	Results are stored for further analyzes	Image is classified into Severe	Pass

Fig. 5.3. Test cases

IV. CONCLUSION

In conclusion, this research project has successfully demonstrated the potential of deep learning, particularly Convolutional Neural Networks (CNNs), as a robust tool for diabetes detection using fundus images. The results affirm the feasibility of employing CNNs to leverage extensive datasets previously curated for physician-interpreted screenings, opening avenues for enhanced and automated diabetes diagnosis. The high flexibility of CNNs, characterised by their low bias and high variance, suggests broader applicability beyond diabetic retinopathy, potentially encompassing various non-diabetic diseases. Notably, visualisations of learned features underscore the interpretability of the model's decision-making process, revealing critical signals in discernible portions of the images. While acknowledging current challenges related to macroscopic features in certain diabetic retinal images, this research provides valuable insights for refining CNN architectures.

The identification of diabetic retinopathy using CNN and machine learning can transform clinical practice. It can aid medical practitioners in making an accurate diagnosis, encourage early action, and stop permanent eyesight loss. Additionally, by automating the screening procedure, it can lessen the strain on healthcare systems, improve access to eye care services, and allow patients to receive prompt treatment. Ultimately, this study contributes to the growing body of evidence supporting the integration of deep learning into medical diagnostics, with the potential to revolutionise the efficiency and accuracy of diabetes detection and pave the way for broader applications in healthcare.

Additionally, the robust performance of Convolutional Neural Networks (CNNs) in diabetic retinopathy detection is further evidenced by the comprehensive analysis of training and validation losses specific to DenseNet121 and DenseNet169 models. Detailed examination of these models' training and validation loss trajectories reveals not only how well they learn intricate patterns within the dataset, but also how well they generalise to new datasets. For both models, DenseNet121 and DenseNet169, the loss curves consistently converge, demonstrating that both models minimise errors during training while maintaining reliable predictive accuracy during validation. As a result of this nuanced evaluation of training and validation losses, it is possible to gain critical insights into the learning dynamics of the models, which enhances their diagnostic accuracy. In addition to demonstrating the reliability and generalisability of CNNs, this analysis reinforces their value in diagnosing diabetic retinopathy and endorses their implementation into routine clinical practice.

4.1 The training loss and the validation loss according to the model DenseNet121

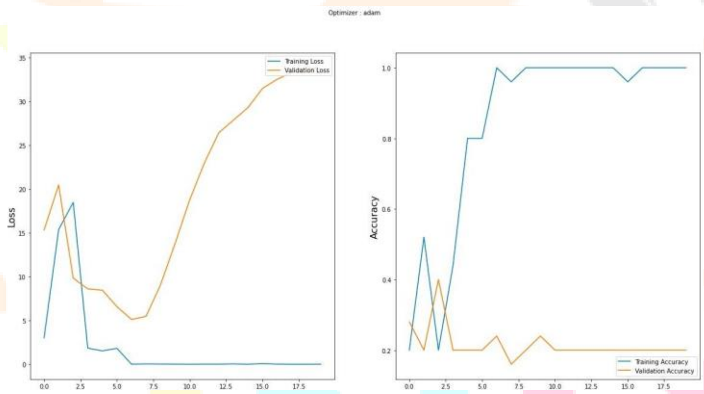

Fig. 6. Loss, Accuracy acc. To DenseNet121

4.2 The training loss and the validation loss according to the model DenseNet169

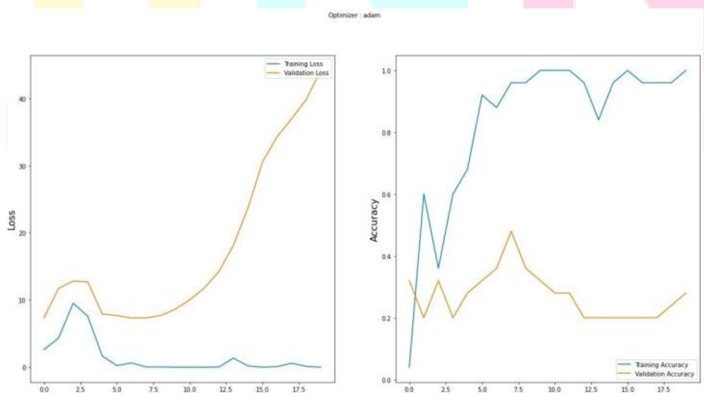

Fig. 7. Loss, Accuracy acc. To DenseNet169

REFERENCES

[1] S.Dua, N. Kandiraju, H. Thompson, "*Design and implementation of a unique blood vessel Detection Algorithm towards Earlydiagnosis of Diabetic Retinopathy*", 2005

[2] H Jiang, K Yang, M Gao,D Zhang "*An interpretable Ensemble Deep learning model for Diabetic Retinopathy diseaseclassification*",2019

[3] M Gandhi, R.Dhanasekaran "*Diagnosis of Diabetic Retinopathy Using Morphological Process and SVM Classifier*",2013

[4] Shu-I Poa,Hong-Zin Lin ,Ke-Hung Chein,Ming-Chena Tai,"*Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network*",2020

[5] Deepthi K Prasad, Vibha L, and Venugopal K R, "*EarlyDetection of Diabetic Retinopathy from Digital Retinal Fundusimages*", December 2015

[6] Amol Prataprao Bhatkar , "*Detection of Diabetic Retinopathy inRetinal images using MLP Classifier*" 2015

[7] Scanlon PH, Wilkinson CP, Aldington SJ, Matthews DR. A Practical manual of diabetic retinopathy management. first ed. Wiley-Blackwell; 2009.

[8] Dubow M, et al. Classification of human retinal microaneurysms using adaptive optics scanning light ophthalmoscope fluorescein angiography. Investig Ophthalmol Vis Sci 2014;55(3):1299–309.

[9] Bandello F, Zarbin MA, Lattanzio R, Zucchiatti I. Clinical strategies in the management of diabetic retinopathy. second ed. Springer; 2019.

[10] Scotland GS, et al. Costs and consequences of automated algorithms versus manual grading for the detection of referable diabetic retinopathy. Br J Ophthalmol 2010; 94(6):712–9.

[11] deng Li. A tutorial survey of architectures, algorithms, and applications for deep learning. APSIPA Trans. Signal Inf Process 2014;3(2):1–29.

[12] V Vasilakos A, Tang Y, Yao Y. Neural networks for computer-aided diagnosis in medicine : a review. Neurocomputing 2016;216:700–8.

[13] Wilkinson CP, et al. Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales. Am Acad Ophthalmol 2003;110(9): 1677–82.

[14] Chen XW, Lin X. Big data deep learning: challenges and perspectives. IEEE Access 2014;2:514–25.

[15] Guo Y, Liu Y, Oerlemans A, Lao S, Wu S, Lew MS. Deep learning for visual understanding: a review. Neurocomputing 2016;187:27–48.

[16] Deng L, Yu D. Deep learning: methods and applications. Found Trends® Signal Process 2014;7(3–4):197–387.

[17] Bakator M, Radosav D. Deep learning and medical diagnosis: a review of literature. Multimodal Technol Interact 2018;2(3):47.

[18] Mookiah M, Acharya UR, Kuang C, Min C, Ng EYK, Laude A. Computer-aided diagnosis of diabetic retinopathy : a review. Comput Biol Med 2013;43:2136–55.

[19] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Commun ACM 2017;60(6).

[20] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. In: IEEE Conference on computer Vision and pattern recognition; 2016. p. 2818–26.

[21] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: IEEE Conference on computer Vision and pattern recognition; 2016. p. 770–8.

[22] Esfahani MT, Ghaderi M, Kafiyeh R. Classification of diabetic and normal fundus images using new deep learning method. Leonardo Electron J Pract Technol 2018; 17(32):233–48.

[23] Li T, Gao Y, Wang K, Guo S, Liu H, Kang H. Diagnostic assessment of deep learning algorithms for diabetic retinopathy screening. Inf Sci 2019;501:511–22.

[24] Abramoff MD, Garvin MK, Sonka M. Retinal imaging and image analysis. IEEE Rev Biomed Eng 2010;3:169–208.

[25] Kauppi T, et al. The DIARETDB1 diabetic retinopathy database and evaluation protocol. In: Proceedings of the British machine vision conference 2007; 2007. p. 1–10.

[26] Leasher, J. L. *et al.* Global estimates on the number of people blind or visually impaired by diabetic retinopathy: A meta-analysis from 1990 to 2010. *Diabetes Care* **39**, 1643–1649 (2016).

[27] International Diabetes Federation. Diabetes atlas. *IDF Diabetes Atlas*, 9th edn. (International Diabetes Federation, Brussels, 2015).

[28] Ting, D. S. W., Cheung, G. C. M. & Wong, T. Y. Diabetic retinopathy: Global prevalence, major risk factors, screening practices and public health challenges: A review. *Clin. Exp. Ophthalmol.* 44, 260–277 (2016).

[29] Thomas, R., Halim, S., Gurudas, S., Sivaprasad, S. & Owens, D. Idf diabetes atlas: A review of studies utilising retinal photography on the global prevalence of diabetes related retinopathy between 2015 and 2018. *Diabetes Research and Clinical Practice*, p. 107840 (2019).

[30] Early Treatment Diabetic Retinopathy Study Research Group. Grading diabetic retinopathy from stereoscopic color fundus photographs-an extension of the modified airlie house classification: Etdrs report number 10. *Ophthalmology* 98, 786–806 (1991).

[31] Owsley, C. *et al.* Perceived barriers to care and attitudes about vision and eye care: Focus groups with older African Americans and eye care providers. *Investig. Ophthalmol. Vis. Sci.* 47, 2797–2802 (2006).

[32] MacLennan, P. A., McGwin, G., Searcey, K. & Owsley, C. A survey of Alabama eye care providers in 2010–2011. *BMC Ophthalmol.* 14, 44 (2014).

[33] Chou, C.-F. *et al.* Barriers to eye care among people aged 40 years and older with diagnosed diabetes, 2006–2010. *Diabetes Care* 37, 180–188 (2014).

[34] Fogel, A. L. & Kvedar, J. C. Artificial intelligence powers digital medicine. *NPJ Digit. Med.* 1, 1–4 (2018).

[35] Gulshan, V. *et al.* Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA* 316, 2402–2410 (2016).

[36] Abràmoff, M. D. *et al.* Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. *Investig. Ophthalmol. Vis. Sci.* 57, 5200–5206 (2016).

[37] Gargeya, R. & Leng, T. Automated identification of diabetic retinopathy using deep learning. *Ophthalmology* 124, 962–969 (2017).

[38] Sayres, R. *et al.* Using a deep learning algorithm and integrated gradients explanation to assist grading for diabetic retinopathy. *Ophthalmology* 126, 552–564 (2019).

[39] Sahlsten, J. *et al.* Deep learning fundus image analysis for diabetic retinopathy and macular edema grading. *Sci. Rep.* 9, 1–11 (2019).

[40] Gulshan, V. *et al.* Performance of a deep-learning algorithm vs manual grading for detecting diabetic retinopathy in India. *JAMA Ophthalmol.* 137, 987–993 (2019).

[41] Ting, D. S. W. *et al.* 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, 2211–2223 (2017).

[42] Takahashi, H., Tampo, H., Arai, Y., Inoue, Y. & Kawashima, H. Applying artificial intelligence to disease staging: Deep learning for improved staging of diabetic retinopathy. *PLS One* 12 (2017).

[43] Soliman, A. Z., Silva, P. S., Aiello, L. P. & Sun, J. K. Ultra-wide field retinal imaging in detection, classification, and management of diabetic retinopathy. *Semin. Ophthalmol.* 27, 221–227 (2012).

[44] Kaines, A., Oliver, S., Reddy, S. & Schwartz, S. D. Ultrawide angle angiography for the detection and management of diabetic retinopathy. *Int. Ophthalmol. Clin.* 49, 53–59 (2009).

[45] Nagasawa, T. *et al.* Accuracy of ultrawide-field fundus ophthalmoscopy-assisted deep learning for detecting treatment-naïve proliferative diabetic retinopathy. *Int. Ophthalmol.* 39, 2153–2159 (2019).