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Advancing Optical Tomography Image Analysis: Exploring Convolutional Neural Network Model Variants for Retinal Damage Detection

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Abstract —**Retina is a vital component of the eye; it plays a crucial role in visual perception. Any damage to the retina can lead to vision impairment and severe ocular diseases. Early detection and accurate diagnosis of retinal conditions is crucial. In the domain of medical image analysis, especially within the scope of retinal imaging, convolutional neural network (CNN)-based deep learning models have exhibited promising results. This paper involves the detection of retinal conditions such as Diabetic Macular Edema (DME), Choroidal Neovascularization (CNV) and Drusen. The paper presents a comparative study of CNN models for the detection of these retinal damages using Optical Coherence Tomography (OCT) images. This study focuses on evaluating the performance of popular CNN architectures, like Residual Networks (ResNet), Dense Convolutional Networks (DenseNet), Inception Networks, Visual Geometry Group (VGG). Also, the paper provides a comparative analysis of different depth variants of deep learning models such as ResNet (18, 50 and 101), DenseNet (121, 169, and 201), Inception-V3, Inception-ResNet-V2, and VGG (16 and 19). These models are assessed on a dataset containing OCT images of Normal, DME, CNV and Drusen retinal conditions. The effectiveness of the models are evaluated using evaluation metrics such as accuracy, precision, recall and F1 score. Additionally, visualizations such as confusion matrix, training accuracy versus validation accuracy plots, training loss versus validation loss plots are utilized to provide a better understanding of the model performance. The idea is to explore the impact of depth on the model performance and understand how deeper models demonstrate an enhanced ability to learn complex features and capture intricate details within the retinal data. Exploring these depth variants aims to provide insights into the advantages and potential trade-offs associated with increasing depth of deep learning models for retinal damage detection tasks.**

Keywords—choroidal neovascularization, deep learning, DenseNet, diabetic macular edema, drusen, Inception networks, medical image analysis, ocular diseases, optical coherence tomography (OCT), ResNet, retina, retinal imaging, VGG.

I. INTRODUCTION

The retina is a thin and delicate layer composed of neurons that plays a crucial role in our ability to perceive the world. The light-sensing part in our eyes converts light into electrical signals, transmitting all visual information to the brain. When it comes to ocular diseases like diabetic retinopathy, diabetic macular degeneration, and glaucoma, early detection has become a critical medical challenge. The conventional approach to retinal damage detection and diagnosis involves manual examination of OCT images by ophthalmologists and retina specialists. However, the analysis can be time consuming and prone to human errors due to the complex nature of retinal structures and subtle variations makes the diagnosis difficult especially in the early stages of disease progression.

Figure 1 shows retinal conditions discussed in the paper: CNV, DME, and Drusen, three common retinal conditions that can lead to significant vision loss [7]. CNV involves abnormal growth of blood vessels under retina. DME refers to fluid accumulation in the macula due to diabetes, and Drusen are deposits that form under the retina. To accurately detect these retinal conditions, doctors use a special imaging technique called OCT. It works by passing light into eyes and capturing the reflections that bounce back from different layers providing high-resolution cross-sectional images of the retinal. This helps ophthalmologists see if there's any abnormal blood vessel growth or fluid build-up in the retina.

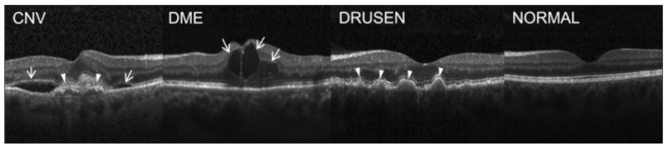

Fig. 1. Optical Coherence Tomography Images

In the recent years the advancements in Artificial Intelligence (AI) and deep learning techniques have shown immense potential and revolutionized medical imaging analysis. Various medical imaging applications, including the analysis of retinal images, have witnessed remarkable results through the use of deep learning models, especially CNNs. By automatically extracting meaningful features from OCT images, these models can aid ophthalmologists and clinicians for diagnosing and monitoring retinal damages more accurately and efficiently. The objective of this work is to investigate diverse CNN architectural variations in accurately identifying and classifying retinal abnormalities which can potentially improve clinical decision making and patient outcomes.

Residual Neural Networks (ResNet) stand out for their skip connections, addressing the vanishing gradient issue in deep networks. Residual blocks allow direct mapping between input and output, even in deeper networks. "Bottleneck blocks" manage computational cost. ResNet excels in computer vision due to its ability to handle depth and complexity. Dense Convolutional Networks (DenseNet) boast extensive connectivity through direct connections between all layers, enhancing information flow. DenseNet blocks consist of densely connected layers; transition layers control expansion and computational costs. Visual Geometry Group (VGG), a simple yet powerful architecture, stacks convolutional layers with small filters for spatial patterns. VGG's depth captures low and high-level information, with fully connected layers as classifiers. Inception Networks, exemplified by Inception V3, use Inception modules to capture multi-scale features. These modules include convolutions of various sizes and auxiliary classifiers to mitigate the vanishing gradient problem. Batch normalization stabilizes training. Inception V3 excels in image classification, often used for transfer learning.

The paper is structured as follows: Section II presents a detailed literature survey. In Section III the design of the experiment is discussed. In Section IV the performance of several variations of DenseNet, ResNet, VGG, and Inception are explained. Section V of the paper concludes the major insights and findings drawn from the study.

II. Literature Review

The convergence of advanced imaging technologies and deep learning algorithms has revolutionized the field of ophthalmology. This literature review offers an overview of research endeavours that explore the fusion of Optical Coherence Tomography (OCT) with deep learning methods to diagnose ocular diseases effectively. Optical Coherence Tomography stands as a pivotal tool, providing intricate cross-sectional retinal images. Its non-invasive nature has transformed the early detection of ailments such as diabetic retinopathy and macular degeneration. Timely intervention is emphasized [1]. Automating Central Serous Retinopathy Detection: Hassan *et al*. [2] put forth a deep learning approach to automate the identification of central serous retinopathy (CSR) using OCT images. Their model displays promising diagnostic potential for CSR. Deep Learning for Macular Edema, introduces DeepOCT, a novel fusion of CNN and Recurrent Neural Networks (RNN) designed to analyze macular edema via OCT images [3]. This model stresses the significance of transparent deep learning architectures in clinical applications. Robust Retinal Disease Classification: Elsharif and Abu-Naser [4] present a CNN model trained on diverse data sources for precise retinal disease classification, showcasing the efficacy of deep learning.

Combining Inception-ResNet Architecture: Yasin *et al.* [5] propose a hybrid Inception-ResNet architecture that skilfully merges the strengths of both architectures. This hybrid model demonstrates enhanced accuracy in grading retinopathy severity and identifying early lesions. Hybrid Features for Disease Identification: Asirvatham *et al*. [6] combined pre-trained CNN features with domain-specific attributes to develop a hybrid deep learning network. This approach offers accurate identification of diverse eye diseases, harnessing the power of both learned and domain-specific features. Innovative Disease Identification with Deep Learning: Kermany *et al*. [7] conducted a seminal study, leveraging deep learning to identify treatable diseases from medical images. Their results underscore the capacity of deep learning to enhance patient outcomes and medical diagnostics. Efficient Vision with Inception Architecture: Szegedy *et al*. [8] introduced an alternative perspective on computer vision using the inception architecture. Experimental findings reveal its potential for efficient object detection and recognition tasks. Enhanced Retinopathy Stage Detection: Novitasari *et al*. [9] devised a hybrid CNN-DELM model for image fundus classification and diabetic retinopathy stage detection. The amalgamation of these techniques demonstrates the power of synergistic deep learning methods. Automatic Myopic Maculopathy Screening: Ye *et al*. [10] pioneered an automated screening system for myopic maculopathy using deep learning models. This study effectively identifies and classifies myopic maculopathy from OCT images, offering significant potential for clinical support. Sheethal *et al*. [11] leveraged advanced image processing techniques and deep learning to develop a robust diagnostic tool for pneumonia using X-ray images, demonstrating significant potential for enhancing medical diagnostics.

Mohan *et al*. [12] conducted a comprehensive analysis comparing various spatial filters for pre-processing CT abdominal images, contributing valuable insights into optimizing image quality enhancement techniques in the field of medical imaging. Corneal Disease Diagnosis through Deep Learning: Elsharif and Abu-Naser [13] developed a multi-disease deep learning neural network, yielding accurate diagnoses for various corneal diseases. Streamlined Eye Disease Prediction: Sundaram and Ravichandran [14] proposed an automated prediction system employing the bag of visual words (BoVW) technique and support vector machine (SVM). Enhanced Retinal OCT Classification: Subramanian *et al*. [15] achieved heightened diagnostic accuracy for retinal conditions through comprehensive training on large OCT image datasets. Kirola *et al*. [16] developed an innovative image-based system utilizing deep learning techniques to predict plant diseases, offering a promising framework for early disease detection and management in agriculture.

Collectively, these studies underscore the transformative potential of combining deep learning methodologies with OCT imaging in ophthalmology, fostering improved disease identification, classification, and patient care. In this study, ten models were implemented and compared: ResNet18, ResNet50, ResNet101, VGG16, VGG19, DenseNet121, DenseNet169, DenseNet201, Inception V3, and Inception-ResNet V2.

III. Design of Experiment

The dataset, derived from Kermany *et al*. [7], is organized into train, test, and validation folders, with subfolders for each category: NORMAL, CNV, DME, and DRUSEN. Comprising 84,495 OCT images in JPEG format, the dataset covers various retinal conditions from multiple sources, captured using the Spectralis OCT system. Out of the four classes, 2500 images each from NORMAL, CNV, DME, and DRUSEN are processed. Images are resized to 256x256 pixels for consistency, labeled, and one-hot encoded for multi-class classification. The dataset is divided into 80% for training and 20% for testing. TensorFlow and Keras construct models with Adam optimizer. Parameters like epochs (8) and batch size (16) are kept uniform. Performance metrics like accuracy, precision, recall, and F1 score are employed for model evaluation, implemented through the Scikit-learn library.

IV. Result and Analysis

In this results analysis section, evaluation of various deep learning model variants are presented. These analyses cover DenseNet, ResNet, VGG, Inception V3, and Inception-ResNetV2 models, aiming to offer a thorough understanding of their effectiveness in retinal damage detection.

A. DenseNet Variants

DenseNet variations, including DenseNet121, DenseNet169, and DenseNet201, were employed to explore their performance across varying model complexities. This allowed an assessment of model's depth impact on classification accuracy, convergence behavior, and generalization capabilities.

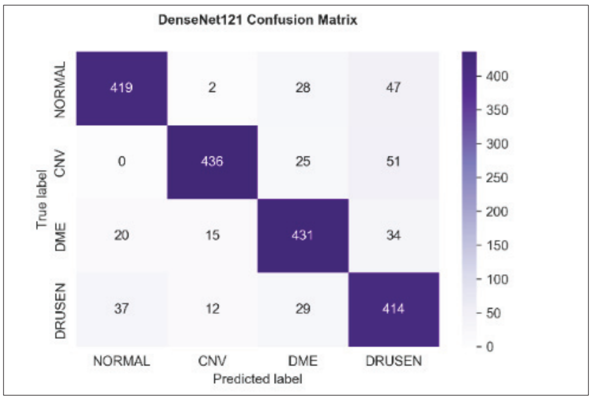

Fig. 2. DenseNet201 confusion matrix

Insights from Confusion Matrix: Figure 2 demonstrates DenseNet201's confusion matrix, where the model exhibits improved performance in the Normal class but displays lower accuracy in DME and DRUSEN classifications when compared to the other variants. The confusion matrix for DenseNet121 shows accurate predictions for each class: 419 Normal, 436 CNV (Choroidal Neovascularization), 431 DME (Diabetic Macular Edema), and 414 DRUSEN images. Similarly, DenseNet169's confusion matrix indicates accurate classifications for 419 Normal, 452 CNV, 343 DME, and 406 DRUSEN images.

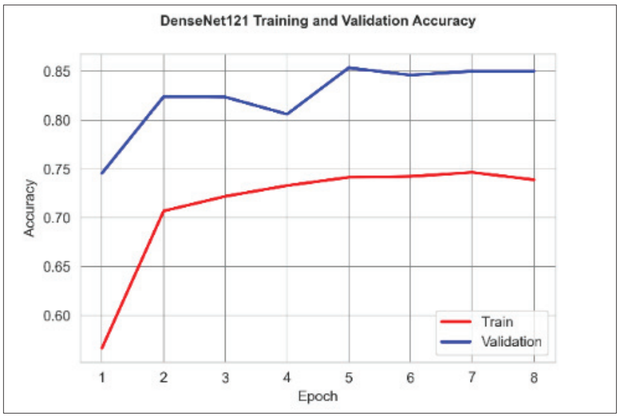

Fig. 3. DenseNet201 training versus validation accuracy

Training Accuracy Trends: Figure 3 illustrates the training and validation accuracy for the models. Regarding training accuracy, DenseNet121 steadily increases to 0.746, while validation accuracy peaks at 0.853, showcasing effective generalization. DenseNet169's training accuracy peaks at 0.773, with validation accuracy maintaining a high level of 0.853. As seen in Figure 3, DenseNet201's training accuracy reaches 0.788, and validation accuracy peaks at 0.869, demonstrating the models' capacity to generalize effectively.

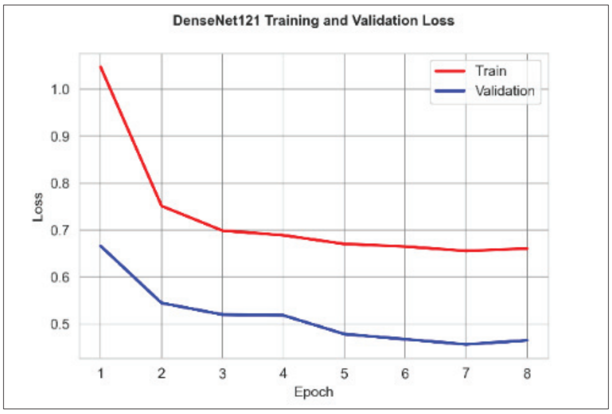

Fig. 4. DenseNet201 training versus validation loss

Loss Patterns: Figure 4 shows that DenseNet201's training loss reaches a minimum of 0.551, and validation loss decreases to 0.385. In terms of training loss, DenseNet121 consistently decreases to a minimum of 0.655, while validation loss drops to 0.456. The training loss of DenseNet169 decreases to 0.578, while the validation loss reaches 0.419. These trends reflect the models' ability to learn from training data and minimize errors during both training and validation.

A. ResNet Variants

The ResNet variants, including ResNet18, ResNet50, and ResNet101, offer insights into their behavior across different depths, allowing exploration of depth's impact on classification accuracy, convergence patterns, and generalization capabilities. Deeper models like ResNet50 and ResNet101 exhibit enhanced aptitude in capturing intricate features and patterns, while relatively shallower ResNet18 may demonstrate a more straightforward decision-making process.

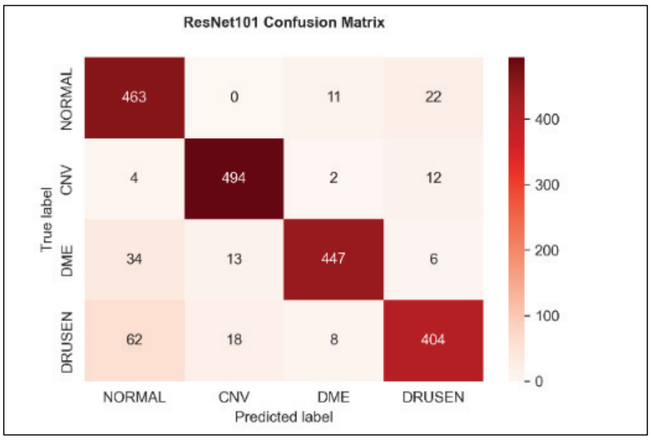

Fig. 5. ResNet101 confusion matrix

Insights from Confusion Matrix: Figure 5 demonstrates the accurate classifications for ResNet101. The confusion matrix for ResNet18 shows accurate classification for 394 Normal, 502 CNV, 415 DME, and 416 DRUSEN samples, reflecting its proficiency in categorizing all classes. Similarly, ResNet50's confusion matrix indicates correct categorization for 384 Normal, 503 CNV, 445 DME, and 434 DRUSEN samples out of 500 in each class.

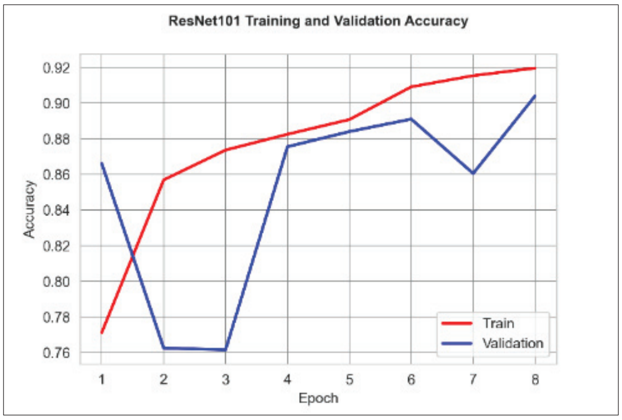

Fig. 6. ResNet101 training versus validation accuracy

Training Accuracy Trends: Figure 6 shows that ResNet101's training accuracy peaks at 0.920, and validation accuracy fluctuates but remains high at 0.904, underscoring effective learning and generalization. Training accuracy for ResNet18 steadily increases to 0.859, and validation accuracy rises to 0.863, illustrating good generalization and effective learning. ResNet50's validation accuracy reaches 0.907, with steady training accuracy growth to 0.933, showcasing efficient learning and generalization.

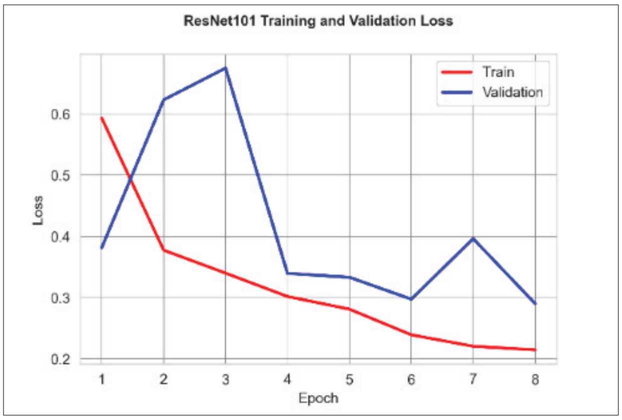

Fig. 7. ResNet101 training versus validation loss

Loss Patterns: Figure 7 shows ResNet101's training versus validation loss, which demonstrates consistent training loss reduction and low validation loss, revealing effective optimization and generalization. Regarding training loss, ResNet18's gradually declines during epochs, while validation loss fluctuates at a low level, indicating successful optimization and generalization. ResNet50 exhibits similar patterns, maintaining low validation loss and slight fluctuations in training loss, implying robust optimization and generalization.

B. VGG Variants

Exploring VGG variants, notably VGG16 and VGG19, offers a valuable opportunity to assess and compare their performance at varying depths. This allows us to evaluate how model depth influences classification accuracy, convergence behaviour, and generalization capabilities through an examination of models with different depths.

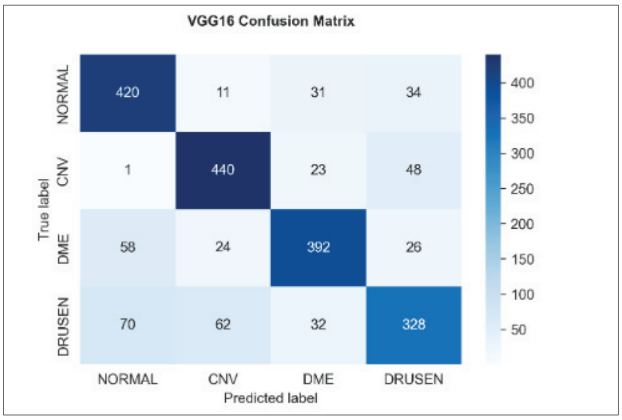

Fig. 8. VGG16 confusion matrix

Insights from Confusion Matrix: Figure 8, demonstrates VGG16 variant confusion matrix. For the "Normal" class, 420 out of 500 samples were correctly classified, while the "CNV" class achieved 440 correct out of 500. The "DME" class had 392 accurate out of 500, and the "DRUSEN" class had 378 accurate out of 500. Similarly, the VGG19 variant's confusion matrix reveals accurate classifications. The "Normal" class had 413 out of 500 samples correctly classified, "CNV" had 423 out of 500 correct, "DME" had 328 out of 500, and "DRUSEN" had 364 out of 500 accurately predicted.

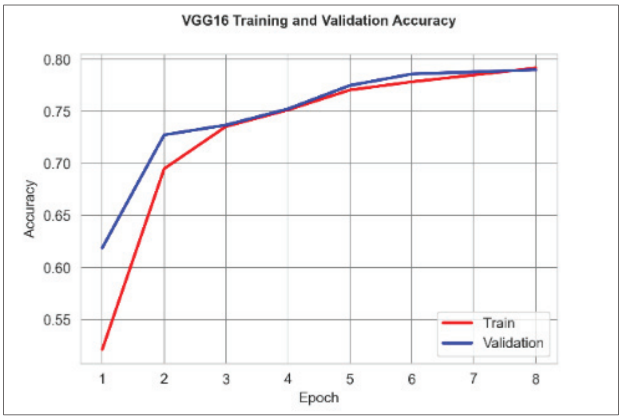

Fig. 9. VGG16 training versus validation accuracy

Training Accuracy Trends: Figure 9. demonstrates an upward trend in VGG16's training accuracy plot, showcasing the model's improved capacity to correctly classify data. Similarly, the validation accuracy plot steadily rises, indicating the model's successful generalization to unseen data. VGG19's training accuracy plots show a similar upward trend, highlighting the model's learning ability. Validation accuracy plots for both variants consistently improve over epochs, indicating effective generalization.

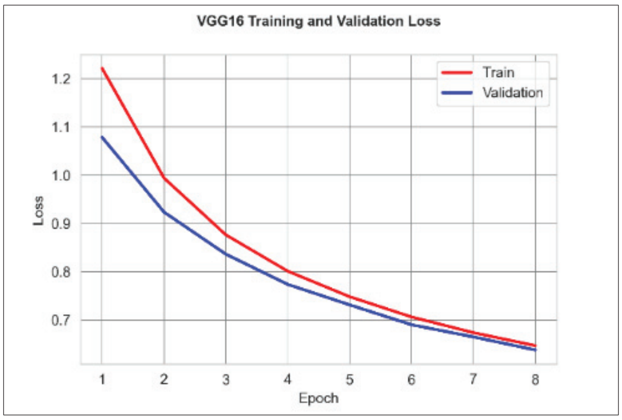

Fig. 10. VGG16 training versus validation loss

Loss Patterns: Figure 10. demonstrates training loss plots for VGG16. Both variants exhibit a decreasing trend, suggesting that the models' errors decrease as training progresses. Validation loss plots also show a steady decline, indicating the models' success in generalizing to new, unseen data. The decreasing training loss for VGG16 suggests efficient information pickup and accurate data fit. Validation loss plots further confirm this successful generalization. Likewise, the decreasing training loss for VGG19 signifies ongoing performance enhancement, echoed in similar patterns within validation loss plots.

In summation, the analysis of VGG16 and VGG19 variants highlights the influence of model depth on performance. Both variants effectively capture and uncover underlying patterns in data, as demonstrated by their increasing training and validation accuracy. The decreasing loss trends in both training and validation further underscore their capacity to learn and generalize effectively.

B. *Inception V3 & Inception-ResNetV2*

Inception V3 and Inception-ResNetV2, variants of Inception networks, offer unique insights into performance. Inception V3, designed for enhanced performance and efficiency, employs parallel convolutional layers of various sizes to capture global and local information. Inception-ResNetV2 builds upon this by integrating residual connections to enhance feature representation and mitigate gradient vanishing.

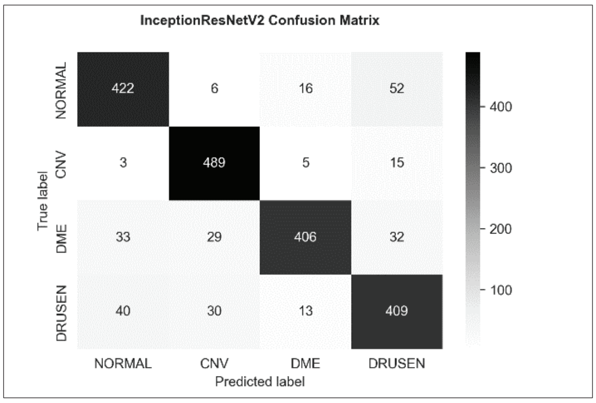

Fig. 11. Inception-ResNetV2 Confusion Matrix

Insights from Confusion Matrix: Figure 11 shows Inception-ResNetV2's confusion matrix, which displays higher accuracy for Normal 422 and CNV 489, but DME 460 exhibits a lower accuracy. The confusion matrix for Inception V3 reveals accurate classifications for Normal 421, CNV 482, and DME 471 classes, but a relatively lower accuracy of 320 for DRUSEN. These findings suggest potential accuracy challenges in classifying DRUSEN and DME samples.

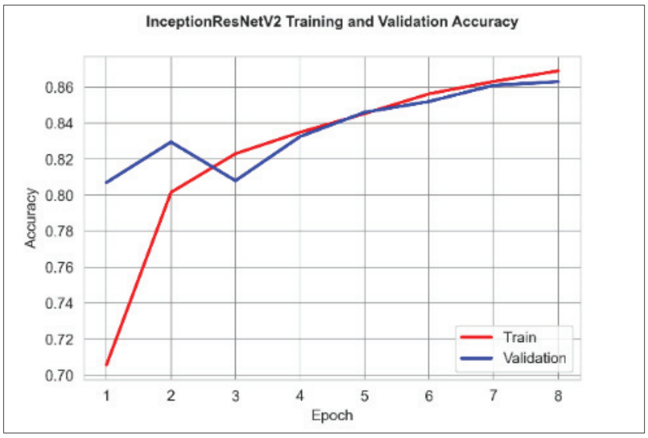

Fig. 12. Inception-ResNetV2 training versus validation accuracy

Training Accuracy Trends: As seen in Figure 12, Inception V3's training accuracy consistently improves across epochs, reaching 89.4%. Validation accuracy exhibits a similar upward trend, peaking at 86.7%. This indicates successful generalization and effective training. In Inception-ResNetV2, training accuracy gradually improves to 86.9%, reflecting its ability to learn. Validation accuracy follows a comparable trend, peaking at 86.3%. These results underscore both models' capacity to capture complex patterns.

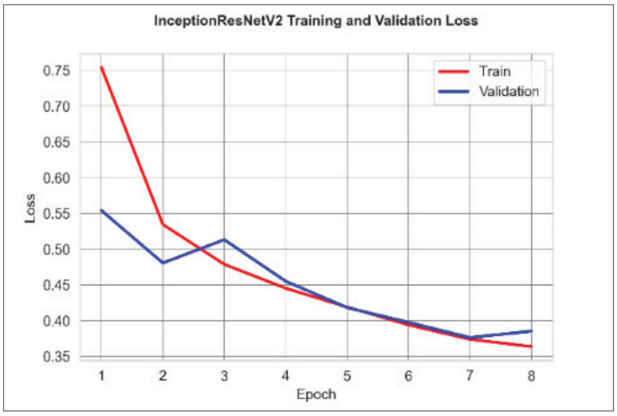

Fig. 13. Inception-ResNetV2 training versus validation loss

Loss Patterns: As seen in Figure 13, throughout training, Inception V3 demonstrates steady decreases in both training and validation loss. Validation loss stabilizes around 0.40, while training loss reaches 0.286, reflecting successful error reduction and generalization. Inception-ResNetV2 also exhibits decreasing training and validation loss trends. Validation loss stabilizes at approximately 0.39, with training loss dropping progressively to 0.364. These outcomes highlight the models' ability to learn patterns and perform well on both training and validation data.

Table 1 displays the performance metrics of different deep learning models assessed for retinal damage detection. The models are assessed on their ability to accurately classify retinal images into four different categories representing various retinal damages. The performance metrics used for evaluation include Accuracy, Precision, Recall, and F1 Score, which are essential for assessing the efficacy of a classifier in medical image analysis.

TABLE 1. PERFORMANCE ANALYSIS OF THE MODELS

Model	Accuracy	Precision	Recall	F1 Score
DenseNet121	0.85	0.8549	0.85	0.8513
DenseNet169	0.8295	0.847	0.8295	0.8298
DenseNet201	0.869	0.8702	0.869	0.8687
VGG16	0.79	0.7896	0.79	0.7884
VGG19	0.764	0.7764	0.764	0.765
InceptionV3	0.847	0.8597	0.847	0.8442
Inception-ResNetV2	0.863	0.8649	0.863	0.8626
ResNet18	0.8635	0.867	0.8635	0.8625
ResNet50	0.883	0.8861	0.8822	0.882
ResNet101	**0.904**	**0.9075**	**0.904**	**0.904**

ResNet101 emerged as the top-performing model in a thorough comparison of numerous deep learning models for the detection of retinal injury, showing higher performance on a number of evaluation metrics. Its excellent precision, recall, accuracy, and F1 score show that it is highly useful at correctly identifying and categorising retinal disorders. The deeper design of ResNet101, which enables it to capture more intricate elements and patterns in retinal images, is responsible for its excellent performance. ResNet101's incorporation of residual connections improves its capacity to address the vanishing gradient issue and enhance gradient flow during training, leading to more reliable and effective learning.

V. CONCLUSION

In this study, a comprehensive evaluation of ten different deep learning models for retinal damage detection is performed. Models from DenseNet 121, DenseNet 169, DenseNet 201, VGG 16, VGG 19, Inception V3, Inception-ResNet V2, ResNet18, ResNet50, and ResNet101 are utilized in the experiment. In order to evaluate each model's accuracy for correctly categorizing retinal images into different damage categories, it is important to gain insight into the advantages and disadvantages of each model at various depths. Each model's accuracy, precision, recall, and F1-score performance measures are carefully examined. The results revealed intriguing differences among the models, shedding light on their unique capabilities at different depths. After extensive analysis, ResNet101 stood out as the best model, with the highest accuracy of 0.904 and balanced precision, recall, and F1-score values all around 0.907. This indicates that ResNet101 exhibited exceptional accuracy and robustness in detecting retinal damage across different categories, particularly when utilizing its depth effectively. As the depth of the model increases, it becomes more computationally expensive, but it often leads to improved results in classifying retinal damage by capturing more intricate details and patterns.

In future research and works, exploring the potential of hybrid models that leverage the unique characteristics of individual models and combine them may lead to even better performance in retinal damage classification tasks by carefully designing and integrating the strengths of multiple models. The findings will contribute to ongoing developments in the field of medical imaging, aiding in the creation of a more accurate and efficient diagnostic tool for retinal diseases. This advancement will enhance patient care by enabling early intervention and potentially preventing irreversible vision loss linked to retinal damage.

REFERENCES

[1] L. M. Aiello, “Perspectives on diabetic retinopathy,” American Journal of Ophthalmology, vol. 136, no. 1, pp. 122–135, Jul. 2003.

[2] S. A. E. Hassan, S. Akbar, S. Gull, A. Rehman and H. Alaska, "Deep Learning-Based Automatic Detection of Central Serous Retinopathy using Optical Coherence Tomographic Images," 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA), pp. 206-211, 2021.

[3] G. Altan, “DeepOCT: An explainable deep learning architecture to analyze macular edema on OCT images,” Engineering Science and Technology, an International Journal, vol. 34, pp 101091, 2022.

[4] A. A. E. F. Elsharif and S. S. Abu-Naser, “Retina Diseases Diagnosis Using Deep Learning,” International Journal of Academic Engineering Research (IJAER), vol. 6, no. 2, pp. 11–37, 2022.

[5] Yasin, Sana, Nasrullah Iqbal, Tariq Ali, Umar Draz, Ali Alqahtani, Muhammad Irfan, Abdul Rehman, “Severity Grading and Early Retinopathy Lesion Detection through Hybrid Inception-ResNet Architecture,” Sensors, vol. 21, no. 20, p. 6933, Oct. 2021.

[6] M. Asirvatham, M. Vijayaraj, T. Manikandan, A. Vignesh, E. E. Nithila and J. N. Jothi, "Hybrid Deep Learning Network to Classify Eye Diseases," 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, pp. 1335-1342, 2022.

[7] Kermany, Daniel S., Michael Goldbaum, Wenjia Cai, Carolina CS Valentim, Huiying Liang, Sally L. Baxter and Alex McKeown, “Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning,” Cell, vol. 172, no. 5, pp. 1122-1131.e9, Feb. 2018.

[8] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, pp. 2818-2826,2016.

[9] Novitasari, Dian Candra Rini, Fatmawati Fatmawati, Rimuljo Hendradi, Hetty Rohayani, Rinda Nariswari, Arnita Arnita, Moch Irfan Hadi, Rizal Amegia Saputra, and Ardhin Primadewi, “Image Fundus Classification System for Diabetic Retinopathy Stage Detection Using Hybrid CNN-DELM,” Big Data and Cognitive Computing, vol. 6, no. 4, pp. 146, Dec. 2022.

[10] Ye, Xin, Jun Wang, Yiqi Chen, Zhe Lv, Shucheng He, Jianbo Mao, Jiahao Xu, and Lijun Shen, “Automatic Screening and Identifying Myopic Maculopathy on Optical Coherence Tomography Images Using Deep Learning,” Translational Vision Science & Technology, vol. 10, no. 13, pp. 10–10, Nov. 2021.

[11] T. R. Sheethal, N. M. Antony and H. NAG, "Diagnosis of Pneumonia utilizing X-rays and other Image Processing techniques based on Containers and Deep Learning," 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), Ravet, India, pp. 1-5, 2022.

[12] R. Mohan, S. P. Chokkalingam, K. Ganapathy, and A. Rama, “Comparative Image Quality Analysis of Spatial Filters for Pre-processing of CT Abdominal Images,” Webology, vol. 18, no. Special Issue 04, pp. 1449–1469, Nov. 2021.

[13] Elsawy, Amr, Taher Eleiwa, Collin Chase, Eyup Ozcan, Mohamed Tolba, William Feuer, Mohamed Abdel-Mottaleb, and Mohamed Abou Shousha. "Multidisease deep learning neural network for the

diagnosis of corneal diseases." American journal of ophthalmology, 2021.

[14] R. Sundaram and K. S. Ravichandran, “An automated eye disease prediction system using bag of visual words and support vector machine,” Journal of Intelligent & Fuzzy Systems, vol. 36, no. 5, pp. 4025–4036, May 2019.

[15] M. Subramanian, K. Shanmugavadivel, O. S. Naren, K. Premkumar and K. Rankish, "Classification of Retinal OCT Images Using Deep Learning," 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-7.

[16] M. Kirola, K. Joshi, S. Chaudhary, N. Singh, H. Anandaram and A. Gupta, "Plants Diseases Prediction Framework: A Image-Based System Using Deep Learning," 2022 IEEE World Conference on Applied Intelligence and Computing (AIC), Sonbhadra, India, pp. 307-313, 2022.