International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Deep Learning-Based Macular Edema Evaluation and Unravelling the Prognostic Landscape for Vision Impairment Risk

Dr. A. V. Ramana[1], B. Sai Lakshman[2], R. Sai Lakshmi[3], A. Vijaya Madhavi[4], B. Lokesh Kumar[5], D. Badrinath[6]

[1]Professor and HOD, CSE, GMR Institute of Technology, Rajam. hod_cse@gmrit.edu.in
[2] bugathasailaxman@gmail.com, [3]reddysailakshm00@gmail.com, [4]vijayamadhavi.027@gmail.com, [5]beelalokeshkumar@gmail.com, [6]badridora466@gmail.com

DOI: https://doi.org/10.55248/gengpi.5.0324.0773

ABSTRACT:

Amidst the current surge in health challenges, macular edema stands out as a significant issue, often complicating various retinal diseases. This condition, characterized by the swelling of the macula, a part of the retina crucial for sharp, central vision, can be a complication of various eye diseases. Conditions such as diabetic retinopathy, age-related macular degeneration, and vascular diseases may lead to macular edema. This condition not only poses a threat to vision but can, in severe cases, lead to blindness. Addressing the complexities of diagnosis and predicting the potential progression to blindness associated with macular edema has become a top priority in clinical research. The integration of advanced imaging technologies and Deep Learning in the assessment of macular edema offers a promising approach to enhance diagnostic precision and predict the risk of blindness. So, in this project a Deep Learning model is to be made which classifies retinal images of a person into various levels of chance of occurrence of blindness. The Deep Learning model uses the algorithms like U-Net, MobileNetV3.

Keywords: Macular Edema, Macular Degeneration, Macular Edema Classification, U-Net, MobileNetV3.

I. INTRODUCTION

Detecting and understanding a vision-related issue known as macular edema is the focus of this project. Macular edema is like a water buildup in a crucial part of the eye called the macula, which is responsible for our central vision. This often happens because blood vessels in the eye are not working properly or there is inflammation. The big problem is that it can lead to distorted vision and even cause people to lose their sight.

Now, why is it so important to investigate this? Well, catching macular edema early is like putting on a superhero cape to save your eyesight. If we can spot it early, we can do something about it before it causes serious harm. This project is all about creating smart tools to help us do just that.

Let us dive a bit deeper into what macular edema is. Imagine your eye is like a camera, and the macula is the lens. When fluid builds up in the macula, it is like water getting into the lens of the camera, making everything blurry and unclear.

Now, the most common reason for this happening is a condition called diabetic retinopathy, which often occurs in people with diabetes. Diabetic retinopathy is like a sidekick to macular edema, making the situation even more complicated. So, we want to develop smart tools that can spot these issues early on and help doctors decide the best way to tackle them. We want to look into the future and predict the risk of blindness. It is like having a crystal ball that helps us see what might happen next. By analysing all the information, we gather – the severity of macular edema, the patient's history, and other factors – we want to create a tool that can predict the risk of losing vision.

This predictive ability is like giving doctors a heads-up about potential dangers, allowing them to act before it is too late. It is all about making sure people with macular edema get the right care at the right time to keep their eyesight safe.

II. LITERATURE SURVEY

Rasti, R., Biglari, A., Rezapourian, M., Yang, Z., & Farsiu, S introduced RetiFluidNet, an automated system aimed at rapidly and accurately identifying eye issues in detailed OCT scans. The objective is to replace the slow and error-prone manual analysis of retinal fluids with an efficient and robust computerized solution. RetiFluidNet demonstrates effectiveness in detecting eye problems across diverse scans, surpassing existing methods. While potential limitations such as variations in image quality are not explicitly mentioned, the model's effectiveness is demonstrated across diverse datasets, outperforming existing methods. RetiFluidNet's adaptability to various OCT devices suggests promising advancements in improving the efficiency of eye treatment management.

Karmbir Khatri, Aditya Rawat, Harshit Chauhan, Kartik Negi, Rishi Mishra focuses on utilizing OCT, a non-invasive imaging test, for diagnosing retinal disorders. Recognizing the time- intensive nature of manually analysing OCT data, the study proposes machine learning models to classify OCT images into four categories: Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), Drusen, and Normal. Two distinct models, employing convolutional neural networks with different layer configurations (three and seven layers), leverage VGG16, ResNet50, and DenseNet121 as feature extractors. The suggested VGG16-based model demonstrates the best performance, achieving high accuracy (0.927), sensitivity (0.927), and specificity (0.932) across multiple classes. Despite not explicitly addressing limitations, the results suggest the potential of these models as additional tools for ophthalmologists, aiding in the efficient classification of retinal conditions.

Barai, N. G., Banik, S., & Samrat researched on RetiNet, an advanced hybrid model blending features from ResNet50 and DenseNet121, is introduced to enhance retinal diagnostics using Optical Coherence Tomography (OCT). Addressing disorders like age-related macular degeneration, the model employs preprocessing techniques on a refined open-source retinal dataset for optimal contrast and noise reduction. Achieving an impressive test accuracy of 98.50%, RetiNet surpasses existing model standards. Although explicit limitations are not detailed, potential challenges may arise in handling real-world variations. The model's innovation extends beyond accuracy, introducing an era of improved reliability and efficiency in medical diagnostics. A web application accompanies RetiNet, aiding doctors in disease prediction during diagnostic procedures. This study represents a significant advancement, combining deep learning and practical applications to transform the landscape of retinal diagnostics.

Guo, X., Li, X., Lin, Q., Li, G., Hu, X., & Che, S addresses the critical need for early screening and treatment of diabetic retinopathy (DR) and diabetic macular edema (DME) to prevent blindness in diabetic patients. It introduces an adaptive attention block (AAB) to enhance feature extraction, with an innovative AABNet framework utilizing MobileNetv2 for feature extraction and separate branches for DR and DME grading. To overcome limited labelled data, the paper proposes a semi supervised learning approach called adaptive teacher-student model, leveraging consistency regularization. Extensive experiments demonstrate AABNet's superiority in multiple grading tasks, including joint DR&DME grading, outperforming state-of-the-art methods on the Messidor and DDR datasets. The model's adaptability, attention mechanism, and semi supervised learning contribute to its improved performance. **Zubair, M., Umair, M., Naqvi, R. A., Hussain, D., Owais, M., & Werghi, N** addresses diabetic macular edema (DME), a condition leading to retinal swelling and potential blindness. To enhance early diagnosis and staging, the proposed model incorporates improved image relative subtraction, Gabor wavelet filter, and advanced fuzzy c- means clustering algorithms for precise localization, blood vessel network extraction, and accurate lesion segmentation. Leveraging Bayesian classification with Gaussian function and expectation maximization for DME grading, the model achieves high accuracies of 96.17% for optic disc detection, 98.60% for fovea localization, 97.85% for exudates segmentation, and 98.80% for DME classification. Comparative analysis showcases the superior performance of the proposed methodology against existing studies, emphasizing its efficiency in computer-assisted diagnosis of DME.

Nazih, W., Aseeri, A. O., Atallah, O. Y., & El-Sappagh, S focusses the critical issue of Diabetic Retinopathy (DR) using an automatic machine learning-based method, leveraging Vision Transformers (ViTs) on the fine-grained annotated diabetic retinopathy (FGADR) dataset. ViTs are optimized with the AdamW optimizer to detect global context in retina images. To handle the imbalanced dataset, the model employs various techniques such as F1-score optimization, data augmentation, class weights, label smoothing, and focal loss. Extensive experiments demonstrate the proposed ViT model's superiority over state-of-the-art CNN algorithms like ResNet50, InceptionV3, and VGG19, achieving impressive F1-score, accuracy, and other performance metrics. The results suggest the potential real-world application of the proposed model in assisting physicians for accurate and personalized DR diagnosis.

Wu, T., Liu, L., Zhang, T., & Wu, X addresses the rising prevalence of diabetic macular edema (DME) and its impact on visual impairment in diabetic retinopathy patients. Utilizing artificial intelligence, a senet154 convolutional neural network with a Squeeze-and-Excitation module is employed for constructing an automatic macular edema classification model using fundus images. The model achieves high AUCs for macular edema risk grades 0, 1, and 2, showcasing its effectiveness in classification. Class activation maps correctly identify focal areas for risk classification. The constructed grading model demonstrates a robust recognition rate for fundus image variations related to diabetic retinopathy, providing valuable insights for large-scale, low-cost screening of macular edema. These findings hold theoretical and practical significance for aiding in the auxiliary diagnosis of macular edema risk grades.

Kumar, A., & Tewari, A. S proposed a method, Squeeze-and- Excitation embedded DenseNet121 (SEDense), introduces an efficient approach for classifying the severity of DME grades in retinal fundus images. Through pre-processing techniques like augmentation and green channel extraction, SEDense achieves an impressive accuracy of 88.35%, outperforming state-of-the-art models in the "Diabetic Retinopathy - Segmentation and Grading Challenge." The proposed model not only provides accurate DME classification but also reduces the burden on ophthalmologists, facilitating timely and efficient diagnosis. The study emphasizes the importance of early identification and treatment in preventing vision loss due to DME, showcasing the potential of deep learning in this medical domain.

Cazañas-Gordón, A., & da Silva Cruz research addresses the complexity of interpreting retinal optical coherence tomography (OCT) images by proposing a novel automatic method for segmenting retinal layers and macular cystoid edema (MCE). The method introduces a Multiscale Attention Gated Network (MAGNet), a lightweight fully convolutional neural network (FCN) that leverages spatial and channel attention gates for fine-grained segmentation and a weighting loss approach to handle class imbalance. The attention gates independently capture spatial and channel correlations, providing a mechanism for improved computational resource allocation, and the proposed loss-weighting approach addresses class imbalance effectively. The study contributes to advancing medical-imaging processing and supports the Green AI initiative.

Altan, G introduces a computer-aided method called DeepOCT to identify macular edema (ME) in eye images using deep learning. DeepOCT is designed to be a simple yet effective algorithm, focusing on high accuracy with fewer parameters. It flattens retinal layers, removes non- retina parts, and uses a lightweight architecture. The model achieved excellent ME identification results, with 99.20% accuracy, 100% sensitivity, and 98.40% specificity. DeepOCT provides a standardized analysis, making it efficient for ophthalmologists to identify ME, even in small pathologies, using a simplified deep learning approach.

Schürer-Waldheim, S., Seeböck, P., Bogunović, H., Gerendas, B. S., & Schmidt-Erfurth presents a novel "PRE-U-net" for automated fovea centralis detection in optical coherence tomography (OCT) scans, addressing it as a pixel-wise regression task. Utilizing 2D B-scans with spatial location information, the deep learning method significantly outperforms existing methods, showcasing improved robustness in localizing the fovea centralis. Tested on 5586 OCT volumes covering healthy subjects and patients with major retinal diseases, including neovascular age-related macular degeneration (nAMD), diabetic macula Edema (DME), and macular edema from retinal vein occlusion (RVO), the proposed model proves valuable for clinical practice and enhances diagnostic precision.

Lim, W. X., Chen, Z., & Ahmed, A focused on analysis of diabetic retinopathy. This work also includes the author's insights in the field of DR. For article selection criteria, the articles which are published between 2017 and 2021 are considered due to rapid advancement in the field. Various Convolutional Neural Networks (CNN) model architectures are adopted mostly for the analysis of diabetic retinopathy. Occlusion, sensitivity analysis, class activation map (CAM), gradient-weighted class activation map (Grad- CAM), layer-wise relevance propagation (LRP), and integrated gradient (IG) are the DR related tasks adopted for this work. The CNN is trained using the fundus images and its respective class labels as input data. There are no explicit lesion features that are fed into the CNN. It compared many of the research papers on diabetic retinopathy and provides further insights to proceed further in the future.

S. Zhu, H. Liu, R. Du, D. S. Annick, S. Chen and W. Qian carried out an investigation on the associativity between the type 2 diabetes and DR severity. Higher contrast retinal photographs taken by a confocal scanning laser ophthalmoscope were used to extract retinal arteriolar and venular tortuosity from both main and branching vessels. It was found that arteriolar and venular tortuosity increased with increasing DR severity, and diabetic patients with more tortuous venules were more likely to suffer from moderate NPDR, severe NPDR, and PDR. It mainly focusses on features, shape, size, and location of the features and the how Diabetic retinopathy causes blindness. Convolutional neural networks like Alex Net, Google Net, VGG-16 are used. This study is approachable towards new technologies in finding the solutions. An accuracy of 96.1% and Precision of 99.7% are achieved. The disadvantage of the paper is that it is just a comparison done on the previous works done in the field of diabetic retinopathy.

Das, D., Biswas, S. K., & Bandyopadhyay precisely describes DR, its symptoms, features, shape, size, and location of the features, and how DR causes blindness. In this paper, some DR features and challenges associated with the respective features are discussed. The paper discusses about hybrid ML-DL based, pure CNN based and CNN-DL based feature extraction and classification techniques and also various unsupervised techniques incorporated with Deep Neural Networks (DNNs). Some of the algorithms used are Alex Net, Google Net, Conv Net, VGG-16, and DCNN. The main advantages of this study are that 1.VGG-16 is used to classify retinal images into good or bad quality and the Datasets like Messidor, stare, drive is used. The model achieved an accuracy of 91%.

Lin, J., Yu, L., Weng, Q., & Zheng, X focused on the already existing work on Retinal Image Quality Assessment for diabetic retinopathy screening. It described the guidelines of retinal image quality evaluation, listed the algorithms applied to verify quality of retinal images, and the advantages and disadvantages of these approaches and some suggestions for future research. Generic features-based approaches, structural features involved approaches like segmentation-based approaches, combinative approaches without segmentation are discussed. Few datasets are inaccurate and had an issue with the noisy data of retinal images, which remained as the biggest disadvantage of this study. Kaggle Eye PACS dataset responded best and for VGG Net architecture with 95.68% accuracy and 97.43% of specificity.

Tsiknakis, N., Theodoropoulos, D., Manikis, G., Ktistakis, E., Boutsora, O., Berto, A., ... & Marias, K studied data about various retina fundus datasets for developing and benchmarking Deep Learning Systems in the context of diagnosing Diabetic Retinopathy is discussed (datasets like Kaggle EyePACS Kaggle APTOS 2019, Messidor& messidor2, IDRiD, DDR and other datasets). The common 5-class grading scale has been presented in which the ophthalmologists utilize to grade a fundus image regarding the DR disease. For model development, many approaches are used like Generic DL approaches, Transfer learning approaches which has shown the best results for using Google Net, Inception V3, Inception V4, Unets, Segmentation based on attention maps, DL approaches based on GANs. Ensemble learning approaches, Interpretable DL approaches have been discussed.

Bora, A., Balasubramanian, S., Babenko, B., Virmani, S., Venugopalan, S., Mitani, A., ... & Bavishi, P work is, in this paper, the internal validation set is evaluated for 7976 eyes and an external validation set for 4762 eyes. The advantages of this paper are that the systems are not dependent and provided more information. Several algorithms for stratifying diabetic retinopathy risk have been described, such as using individual risk factors to reduce screening frequency. Additionally, deep learning was applied to color fundus photographs to predict progression by two or more steps on the Early Treatment Diabetic Retinopathy Study scale. In the internal validation set, the AUC of available risk factors was 0·72, which improved to 0·81 after combining the deep-learning system. But, the limitations of this paper are that some risk factors are not included in the datasets. The model shown even the person with high risk of Dr is suffering with DR. **El-Ateif, S., & Idri,** evaluated and compares the performances of the single-modality models and determines the best and less sensitive model on the APTOS19 and Messidor-2 datasets. It has a readable format which is very clear and conveys the message clearly. The disadvantages of this survey are that DL models are trained on a single modality and the Messidor2 dataset has fewer instance

and higher-class imbalance. VGG-19, InceptionV3, Dense Net like DL architectures are adopted for this survey paper and APTOS19 and Messidor-2 datasets are used for DR binary classification. The results are like accuracy for VGG19 model was 97.49% and 91.20% with the datasets respectively. The Inception-V3 model has performed out well and gave the best results for the respective Diabetic Retinopathy classification.

Stolte, S., & Fang, R summarized over 150 papers that automate grading of Diabetic Retinopathy. It details the key retinal datasets and imaging modalities, and machine learning pipelines. Superior methods used deep learning systems to identify and segment the lesions and grade images. It includes novel DL pipelines, overview imaging and ML processes, and discuss all tasks for grading DR. This discussion facilitates clinical implementation of state- of-the-art systems. This one is different from past works made on DR as it includes novel DL pipelines and ML processes. Particularly, it discussed all the tasks for grading several stages of Diabetic Retinopathy. No datasets were considered to identify the diabetic retinopathy or to analyze the disease, which remained as a disadvantage for this paper. Coming to the performance part, the model achieved accuracy of 93% is achieved by neural network architecture. It concludes that DL systems offer potential to DR identification and classification.

Katada, Y., Ozawa, N., Masayoshi, K., Ofuji, Y., Tsubota, K., & Kurihara, T study is approved by the institutional review board of the Keio University School of Medicine. All the training and clinical validation images were graded for DR by three licensed Japanese ophthalmologists. The DR severity (none, mild, moderate, severe, or proliferative) was graded according to the International Clinical Diabetic Retinopathy scale. All the images were graded based on one posterior fundus image with a 40–50 degrees field of view. Those with varying grading results were repeatedly graded until they finally matched until constant results were obtained. Images of poor quality were eliminated. In this study, the SVM architecture exhibited a superior performance compared with the NN architecture. A data set consisting of 35,126 open-source American clinical fundus images was used. AI model gave a sensitivity of 81.5% and specificity of 71.9% for American dataset. Japanese dataset gave a sensitivity of 90.8% and specificity of 80.0%.

Liu, R., Wang, X., Wu, Q., Dai, L., Fang, X., Yan, T., ... & Zhang, P work includes deep learning approaches in DR image quality assessment and grading are presented. It provided deep learning approaches in DR image quality assessment and grading. This provided the DeepDRiD dataset, performance evaluation, top methods, and results. The deep learning Convolutional architectures like VGG, Res Net, Cat Boost, XG boost models are used. The limitations of this study are that, several experts jointly evaluated the images and disagreed some of them. The supervised models are not performing up to the mark. The advantage of the paper is that Correlation between different fundus images was considered, and better accuracy was achieved. Almost all teams in this challenge used deep learning models as the main network framework to solve this problem. The results also show that the deep learning models do achieve good results, which demonstrates the great potential of deep models in this problem.

Ruamviboonsuk, P., Tiwari, R., Sayres, R., Nganthavee, V., Hemarat, K., Kongprayoon, A., ... & Webster, D. R. made a study on national diabetic retinopathy screening programmed conducted in Thailand. This is a study to evaluate the real-world performance and feasibility of deploying a deep-learning system into the health- care system of Thailand. Deep learning systems are used to carry out several eye related disease diagnoses. It is a real time survey- based analysis and it had produced a better accurate result. The absence of electronic medical records. The quality of retinal images was not all good. Every image analyzed by the deep-learning systems was also over-read for safety by regional retinal specialists and this study is the largest real-world validation to-date of a deep- learning system for eye screenings, having screened more than 7000 patients across both urban and rural care settings. The deep-learning system had similar accuracy to Thai retina specialist over-readers with significantly higher sensitivity. The deep learning models out performed with an accuracy of 94.7%.

Abdelsalam, followed a methodology for early detection of DR subjects. The proposed methodology is capable of accurate classification of the diabetic without DR and Non-proliferative diabetic retinopathy subjects. This methodology depends on using written custom programs and a plugin for MATLAB and Fiji based Image-J software with a supervised artificial neural network. This technique achieves high accuracy, resolution, specificity, and precision with only a short time needed for diagnosis. Rather than the usage of standard available functions, which had not good results in case of low image resolution or quality. The resulted divergent numerical datasets are used to train the supposed ANN. The suggested methodology achieved 97% accuracy. The disadvantage if this study is that though it reached an accuracy of 97%, It is not much advantageous as it considered a very small dataset. And finally, it has drawn the conclusions that out of 100, it found 40 eyes were normal,30 eyes were without DR,30 were NPDR eyes.

III. METHODOLOGY

Data Preprocessing:

Since, the data was very undistributed across various classes, the dataset size has been limited to 17,500 Training images. Class - 3, Class-4 have been Augmented by 4 times, 5 times using ImageDataGenerator (rotation_range=5, shear_range=0.1, zoom_range=0.1, horizontal_flip=True) function from keras. preprocessing. image library, making class 3 a total of 3492 and class 4 a total of 3540 images. Finally, the dataset consists of 3500 images from each class. The images are then resized to 128*128.

Flow Chart:

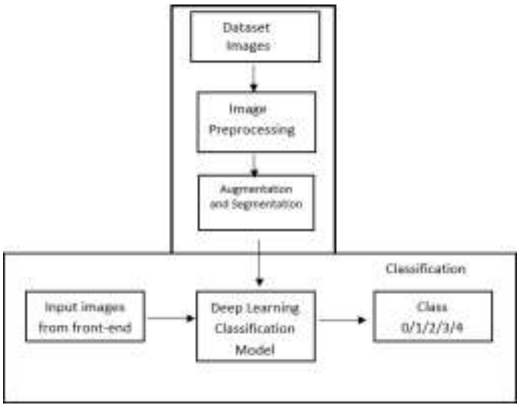

Fig 1: Flow diagram for model

The above figure represents the process flow of the model right from the start. It includes two different phases of the model which are the training phase and the prediction phase.

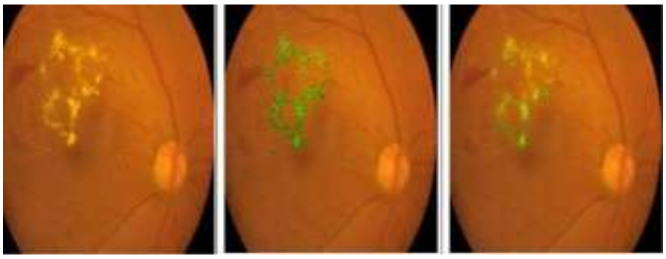

Fig 2: images of retinal segmentation

U-Net: It is a convolutional neural network renowned for biomedical image segmentation. Its unique U-shaped architecture comprises an encoder for feature extraction and a decoder for spatial reconstruction. Skip connections facilitate information flow between encoder and decoder, preserving fine details. The final layer produces probability maps for segmentation. U-Net's simplicity, effectiveness, and adaptability have led to widespread adoption in biomedical and diverse image segmentation tasks.

MobileNetV3:

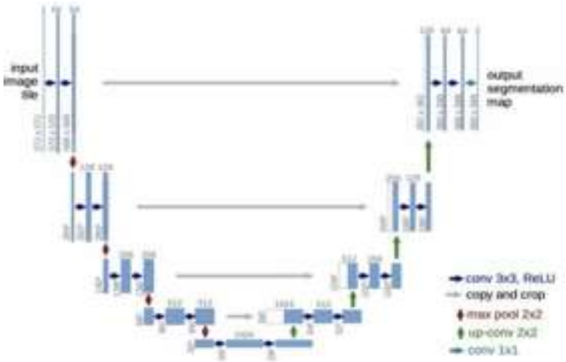

Fig 3: Architecture of U-Net

MobileNetV3 is a convolutional neural network architecture designed for efficient and lightweight deep learning inference on mobile and embedded devices. It is an improvement over the original MobileNet architecture, aimed at providing better performance while maintaining a small model size and low computational complexity.

Depthwise Separable Convolutions: MobileNetV3 heavily utilizes depthwise separable convolutions, which consist of two separate layers: depthwise convolution and pointwise convolution. This factorizes the standard convolution into a depthwise operation and a 1x1 pointwise operation, reducing the number of parameters and computations required.

Inverted Residuals with Linear Bottlenecks: MobileNetV3 introduces a concept called "inverted residuals" which allows for better representation power with fewer parameters. It uses linear bottleneck layers followed by non-linear activations to capture more complex features effectively.

Linear Bottleneck Layer: Instead of directly applying non-linear activation functions after the depthwise convolution, MobileNetV3 adds a linear bottleneck layer before applying the activation. This linear bottleneck reduces the model's reliance on non-linearities and helps in preserving information flow.

Width Multiplier and Resolution Multiplier: MobileNetV3 introduces two hyperparameters, width multiplier and resolution multiplier, that allow the model's size and computational complexity to be scaled according to the specific requirements of the application. The width multiplier scales the number of channels in each layer, while the resolution multiplier scales the input resolution.

IV. RESULTS AND DISCUSSION

In our survey of existing literature pertaining to the project on macular edema classification, we discovered a range of studies highlighting the efficacy of Deep Learning models, particularly U-Net and MobileNetV3, in accurately categorizing retinal images into different classes associated with macular edema severity. With the potential to classify images into one of the five classes representing varying degrees of macular edema severity, these Deep Learning frameworks present a robust foundation for our project's objective of enhancing diagnostic precision and predicting the risk of blindness.

The Deep Learning Model U-Net on the dataset gave an accuracy of 94.62% and classified the given input images of the two retinas as the stages of Macular Edema.

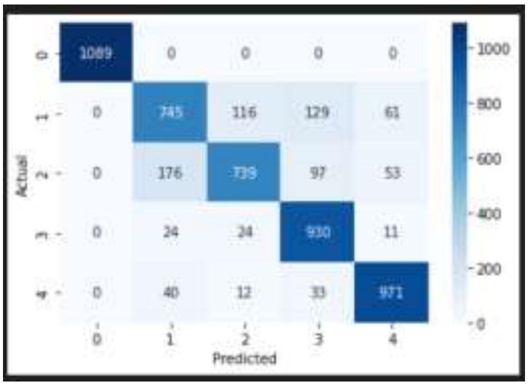

Fig 4: Heat Map for the class labels

The above figure is the output of the confusion matrix represents the performance of the classification model on a set of test data where true values are known. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class.

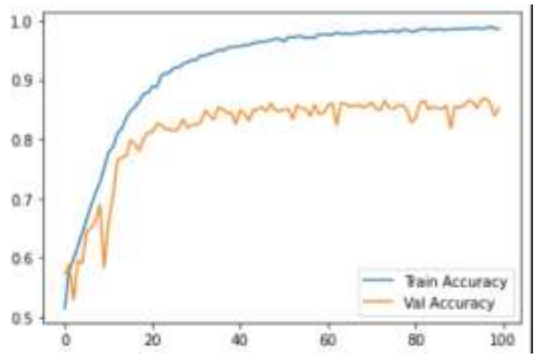

Fig-5: Plot for the training and Validation accuracy

V. CONCLUSION

In Conclusion, this project is to create a model that can find macular edema early, understand how bad it is, and help doctors make the best decisions for their patients. Our goal is to make this deep learning model easy to use in real-world situations, making a positive impact on the lives of people facing the threat of vision loss.

REFERENCES:

1. Rasti, R., Biglari, A., Rezapourian, M., Yang, Z., & Farsiu, S. RetiFluidNet: A Self-Adaptive and Multi-Attention Deep Convolutional Network for Retinal OCT Fluid Segmentation. *IEEE Transactions on Medical Imaging*.

2. Khatri, K., Rawat, A., Chauhan, H., Negi, K., & Mishra, R. DIAGNOSIS OF RETINAL DISEASES FROM OCT IMAGES USING DEEP LEARNING ALGORITHMS.

3. Barai, N. G., Banik, S., & Shamrat, F. J. M. A Novel Fusion Deep Learning Approach for Retinal Disease Diagnosis Enhanced by Web Application Predictive Tool.
4. Guo, X., Li, X., Lin, Q., Li, G., Hu, X., & Che, S. (2023). Joint grading of diabetic retinopathy and diabetic macular edema using an adaptive attention block and semisupervised learning. *Applied Intelligence*, *53*(13), 16797-16812.
5. Zubair, M., Umair, M., Naqvi, R. A., Hussain, D., Owais, M., & Werghi, N. (2023). A comprehensive computer-aided system for an early-stage diagnosis and classification of diabetic macular edema. *Journal of King Saud University- Computer and Information Sciences*, *35*(8), 101719.
6. Nazih, W., Aseeri, A. O., Atallah, O. Y., & El-Sappagh, S. (2023). Vision Transformer Model for Predicting the Severity of Diabetic Retinopathy in Fundus Photography-Based Retina Images. *IEEE Access*, *11*, 117546-117561.
7. Wu, T., Liu, L., Zhang, T., & Wu, X. (2022). Deep learning- based risk classification and auxiliary diagnosis of macular edema. *Intelligence-Based Medicine*, *6*, 100053.
8. Kumar, A., Tewari, A. S., & Singh, J. P. (2022). Classification of diabetic macular edema severity using deep learning technique. *Research on Biomedical Engineering*, *38*(3), 977-987.
9. Cazañas-Gordón, A., Parra-Mora, E., & Cruz, L. A. D. S. (2021). Ensemble learning approach to retinal thickness assessment in optical coherence tomography. *IEEE Access*, *9*, 67349-67363.
10. Altan, G. (2022). DeepOCT: an explainable deep learning architecture to analyze macular edema on OCT images. *Engineering Science and Technology, an International Journal*, *34*, 101091.
11. Schürer-Waldheim, S., Seeböck, P., Bogunović, H., Gerendas, B. S., & Schmidt-Erfurth, U. (2022). Robust Fovea Detection in Retinal OCT Imaging Using Deep Learning. *IEEE Journal of Biomedical and Health Informatics*, *26*(8), 3927- 3937.
12. Lim, W. X., Chen, Z., & Ahmed, A. (2022). The adoption of deep learning interpretability techniques on diabetic retinopathy analysis: a review. *Medical & Biological Engineering & Computing*, *60*(3), 633-642.
13. Zhu, S., Liu, H., Du, R., Annick, D. S., Chen, S., & Qian,
14. W. (2020). Tortuosity of retinal main and branching arterioles, venules in patients with type 2 diabetes and diabetic retinopathy in china. *IEEE Access*, *8*, 6201-6208.
15. Das, D., Biswas, S. K., & Bandyopadhyay, S. (2023). Detection of diabetic retinopathy using convolutional neural networks for feature extraction and classification (DRFEC). *Multimedia Tools and Applications*, *82*(19), 29943- 30001.
16. Lin, J., Yu, L., Weng, Q., & Zheng, X. (2020). Retinal image quality assessment for diabetic retinopathy screening: A survey. *Multimedia Tools and Applications*, *79*, 16173-16199.
17. Tsiknakis, N., Theodoropoulos, D., Manikis, G., Ktistakis, E., Boutsora, O., Berto, A., ... & Marias, K. (2021). Deep learning for diabetic retinopathy detection and classification based on fundus images: A review. *Computers in biology and medicine*, *135*, 104599.
18. Bora, A., Balasubramanian, S., Babenko, B., Virmani, S., Venugopalan, S., Mitani, A., ... & Bavishi, P. (2021). Predicting the risk of developing diabetic retinopathy using deep learning. *The Lancet Digital Health*, *3*(1), e10-e19.
19. El-Ateif, S., & Idri, A. (2023). Eye diseases diagnosis using deep learning and multimodal medical eye imaging. *Multimedia Tools and Applications*, 1-46.
20. Stolte, S., & Fang, R. (2020). A survey on medical image analysis in diabetic retinopathy. *Medical image analysis, 64*, 101742.
21. Katada, Y., Ozawa, N., Masayoshi, K., Ofuji, Y., Tsubota, K., & Kurihara, T. (2020). Automatic screening for diabetic retinopathy in interracial fundus images using artificial intelligence. *Intelligence-Based Medicine*, *3*, 100024.