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Diabetic Retinopathy Classification Using Deep And Transfer Learning Models

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Abstract:
This study investigates the effectiveness of various deep learning and transfer learning models in classifying diabetic retinopathy (DR) using datasets including APTO, Messidor, and RFMiD. A comprehensive analysis is conducted using a range of state-of-the-art CNN architectures, including ResNet50, ResNet152, ResNet101, CNN, AlexNet, InceptionV3, InceptionResNetV2, Deep Residual Network, DenseNet201, DenseNet121, and Xception. While the base paper primarily focused on conventional CNN architectures, we extend this exploration by incorporating the Xception model. Our findings reveal that Xception achieves exceptional accuracy, surpassing 99% in DR classification tasks. This success is attributed to its innovative depthwise separable convolutions and robust feature learning capabilities. Comparative analysis demonstrates that Xception outperforms other architectures, showcasing its potential in enhancing diagnostic accuracy for DR. By leveraging advanced deep learning techniques and exploring diverse model architectures, this study contributes to the optimization of medical image analysis in the context of diabetic retinopathy. The results underscore the significance of incorporating novel techniques like Xception to further advance the performance and efficacy of DR classification systems.

Index terms – *Diabetic Retinopathy, Deep Learning, Transfer Learning, CNN, Xception, Inception, ResNet, AlexNet, Deep Residual Network.*

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I. Introduction

Diabetic Retinopathy (DR) is a well- known vision- hanging complication of diabetes. According to the International Diabetes Federation (IDF) in 2019 (1), roughly 463 million grown-ups (20- 79 times) were living with diabetes. By 2045, the number of grown- ups living with diabetes is anticipated to rise to 700 million. One out of three people with diabetes has diabetic retinopathy, and one in ten is anticipated to have a vision- hanging problem. Therefore, the early discovery of diabetic retinopathy is important to help sight impairment and blindness caused by diabetic retinopathy. To diagnose the inflexibility of diabetic retinopathy, an ophthalmologist analyzes and grades the fundus image into one of five grades ranging from zero to four. The grades from zero to four correspond to the inflexibility position, normal, mild, moderate, severe, or proliferative. The grading of a fundus image is grounded on the presence and the number of different lesions similar as microaneurysms, soft exudates, hard exudates, and hemorrhages(2, 3). Several workshop fuse the five grades to double bracket, non-referable(Normal and Mild) versus referable(Moderate, Severe, and Proliferative)(3, 4, 5, 6). Several deep neural network infrastructures(8, 9, 10) were introduced and dived numerous bracket tasks in medical operations. also, CNNs proved excellent performance in DR bracket(3, 11, 12). still, these deep literacy models remain lower interpretable to humans, which leads to a lack of mortal trust in their decision. therefore, explaining why CNN models produce that specific marker is pivotal to erecting trust between these models and humans. A pioneering system for model interpretation is Class Activation Charts(CAM)(13). CAM proposed a linearly weighted combination of the point maps uprooted from the last subcaste according to its significance. still, CAM posed some armature constraints, as the model should always have a global normal pooling subcaste before the bracket subcaste. This study explores diabetic retinopathy bracket using colorful deep and transfer literacy models similar as ResNet50, ResNet152, ResNet101, CNN, Alex Net, InceptionV3, InceptionResNetV2, Deep Residual Network, DenseNet201, DenseNet121, and Xception. The disquisition aims to assess the effectiveness of these models in diabetic retinopathy bracket tasks. The bracket delicacy of being diabetic retinopathy(DR) discovery models using conventional CNN infrastructures is sour due to limitations in point birth and representation capabilities. Diabetic retinopathy is a leading cause of blindness worldwide, challenging accurate and timely opinion. still, current DR bracket styles frequently warrant perfection, hindering effective case operation and treatment. Individuals with diabetes are particularly vulnerable to diabetic retinopathy, which can lead to severe vision impairment if not detected and treated instantly. Also, healthcare providers and medical professionals are challenged by the inefficiencies of being bracket models in directly diagnosing DR. Inaccurate or delayed opinion of diabetic retinopathy can affect in unrecoverable vision loss and increased healthcare costs associated with advanced treatments or interventions. Also, it imposes significant cerebral and socioeconomic burdens on affected individualities and their families. We propose to probe the efficacity of advanced deep and transfer literacy models, including ResNet50, ResNet152, ResNet101, CNN, Alex Net, InceptionV3, InceptionResNetV2, Deep Residual Network, DenseNet201, DenseNet121, and Xception, in perfecting the bracket delicacy of diabetic retinopathy. By using these state- of- the- art ways, we aim to enhance the perfection and trustability of DR opinion, eventually perfecting patient issues and reducing the burden on healthcare systems.

II. Literature Survey

Diabetic retinopathy (DR) is a leading cause of blindness worldwide, affecting individuals with diabetes. Over the years, various studies have been conducted to develop and validate methods for the detection and grading of DR using retinal fundus photographs. Herein, we present a literature survey covering significant contributions in this field.

Early studies in the early 1990s laid the groundwork for classifying DR. The Early Treatment Diabetic Retinopathy Study (ETDRS) Research Group introduced a grading system based on stereoscopic color fundus photographs, extending the modified Airlie House classification [2]. This work provided a standardized framework for evaluating DR severity.

Advancements in deep learning have revolutionized the detection and diagnosis of DR. Gulshan et al. developed and validated a deep learning algorithm for DR detection using retinal fundus photographs, demonstrating promising results [3]. Subsequent studies further refined deep learning models for DR detection and related eye diseases, catering to multiethnic populations with diabetes [5]. These efforts have significantly improved the efficiency and accuracy of DR screening.

Sahlsten et al. proposed a deep learning approach for DR and macular edema grading, leveraging fundus image analysis [6]. Their work highlights the potential of deep learning in automating the grading process, thereby facilitating timely interventions for patients with DR.

Explainability of deep learning models is crucial for clinical acceptance and trust. Chetoui and Akhloufi addressed this by developing an explainable DR system using EfficientNet, enhancing interpretability and providing insights into model decisions [11]. Explainable AI techniques contribute to the transparency and reliability of automated DR grading systems.

Cross-disease attention networks have emerged as a promising approach for joint DR and diabetic macular edema (DME) grading. Li et al. introduced CANet, a cross-disease attention network that improves the accuracy of DR and DME grading through effective feature representation [12]. This integrative approach enhances diagnostic capabilities, particularly in detecting comorbidities associated with DR.

Benchmark datasets play a crucial role in evaluating and comparing DR detection algorithms. Zhou et al. proposed a benchmark for studying DR, encompassing segmentation, grading, and transferability tasks [18]. Such benchmarks facilitate the development of robust and generalizable algorithms, fostering advancements in the field of DR diagnosis.

In summary, significant progress has been made in the detection and grading of DR using retinal fundus photographs. From traditional classification systems to state-of-the-art deep learning models, researchers have continuously improved the accuracy and efficiency of DR screening. Explainable AI techniques and cross-disease attention networks further enhance the interpretability and diagnostic capabilities of automated DR grading systems. Benchmark datasets play a crucial role in evaluating algorithm performance and fostering advancements in the field. Moving forward, interdisciplinary collaboration and ongoing research efforts are essential for addressing the challenges associated with DR diagnosis and management.

III. Methodology

Proposed Work:

The proposed system aims to enhance the accuracy of diabetic retinopathy (DR) classification through the integration of advanced deep and transfer learning models. Leveraging datasets such as APTO, Messidor, and RFMiD, the system will explore various CNN architectures including ResNet50, ResNet152, ResNet101, CNN, AlexNet, InceptionV3, InceptionResNetV2, Deep Residual Network, DenseNet201, DenseNet121, and Xception. By employing these state-of-the-art techniques, the system seeks to address the limitations of existing DR detection methods, particularly in feature extraction and representation. Through rigorous experimentation and evaluation, the proposed system aims to achieve higher classification accuracy, ultimately improving the reliability of DR diagnosis. This enhancement is crucial for timely intervention and treatment, reducing the risk of vision loss and associated healthcare burdens. Additionally, the system's scalability and adaptability ensure its potential for broader application in healthcare settings, supporting clinicians and healthcare providers in delivering effective patient care.

System Architecture:

In the system architecture utilizing datasets such as APTO, Messidor, and RFMID, image processing is conducted to preprocess retinal fundus images. Models including ResNet50, ResNet152, ResNet101, CNN, AlexNet, InceptionV3, InceptionResNetV2, Deep Residual Network, DenseNet201, DenseNet121, and Xception are employed for predicting results. These models leverage deep learning techniques to analyze retinal images and classify diabetic retinopathy severity levels. By utilizing advanced architectures and extensive datasets, the system achieves accurate predictions, aiding in the early detection and management of diabetic retinopathy.

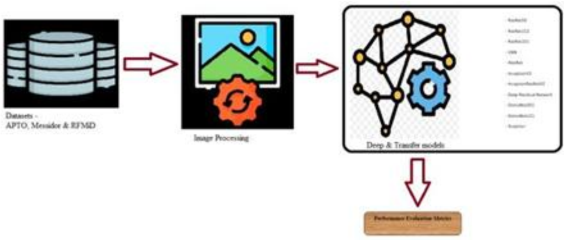

Fig 1 Proposed Architecture

Dataset Collection:

The exploration of datasets for diabetic retinopathy (DR) research involves the collection and analysis of various datasets, including APTO, Messidor, and RFMiD. APTO, the Asian Pacific Tele-Ophthalmology Society (APTO) Diabetic Retinopathy Database, comprises retinal fundus images collected from diabetic patients across the Asian Pacific region. The dataset provides a diverse representation of retinal pathology, contributing to the development and evaluation of DR detection algorithms. Messidor, on the other hand, is a publicly available dataset consisting of retinal images obtained from diabetic patients. It includes annotations for DR severity levels, facilitating the training and validation of machine learning models for automated DR screening. RFMiD, the Retinal Fundus images for Multiple Instance Detection dataset, is designed specifically for the detection of multiple retinal diseases, including diabetic retinopathy. It contains high-quality retinal images with annotations for various abnormalities, enabling comprehensive analysis and evaluation of DR detection algorithms. Collectively, these datasets play a crucial role in advancing research on diabetic retinopathy detection and management, providing researchers with valuable resources for algorithm development, validation, and benchmarking.

Image Processing:

In image processing for diabetic retinopathy detection, the Image Data Generator tool is employed to perform various transformations on retinal fundus images. Firstly, images are rescaled to ensure uniformity in pixel values, aiding in model training by mitigating variations in input data. Shear transformation is applied to introduce controlled deformations, simulating the effects of oblique viewing angles commonly encountered in clinical settings.

Zooming is implemented to create variations in image scale, enabling the model to learn robust features across different magnifications. Horizontal flip augmentation is utilized to augment the dataset by generating mirror images, enhancing model generalization and reducing overfitting. Additionally, reshaping the image to a standard size ensures consistency in input dimensions, facilitating seamless integration with deep learning architectures.

Through these image processing techniques, the dataset's diversity is enhanced, improving the model's ability to generalize to unseen data. By introducing controlled variations in the training set, the model becomes more robust to real-world variations encountered during inference, ultimately enhancing its performance in detecting diabetic retinopathy from retinal fundus images.

Algorithms:

- ResNet50: ResNet50 is a convolutional neural network architecture consisting of 50 layers. It introduces residual connections to address vanishing gradient problems, enabling deeper networks. We use it in this project for its balance between depth and computational efficiency, suitable for diabetic retinopathy classification tasks.
- ResNet152: ResNet152 is an extension of the ResNet architecture with 152 layers. It utilizes residual connections to enable training of extremely deep neural networks. In this project, we employ ResNet152 for its ability to capture intricate features in retinal images, enhancing diabetic retinopathy classification accuracy.
- ResNet101: ResNet101 is a variant of the ResNet architecture with 101 layers. It incorporates residual connections to facilitate the training of deep neural networks. We utilize ResNet101 in this project for its depth and capability to extract complex features, contributing to improved diabetic retinopathy classification performance.
- CNN: CNN (Convolutional Neural Network) is a deep learning architecture designed for image classification tasks. It consists of convolutional layers followed by pooling and fully connected layers. We employ CNNs in this project for their effectiveness in learning spatial hierarchies of features from retinal images, aiding in diabetic retinopathy classification.
- AlexNet: AlexNet is a deep convolutional neural network architecture designed for image classification tasks. It consists of multiple convolutional and pooling layers, followed by fully connected layers. We use AlexNet in this project for its pioneering design and effectiveness in learning discriminative features from retinal images for diabetic retinopathy classification.
- InceptionV3: InceptionV3 is a deep convolutional neural network architecture known for its efficient use of computational resources. It employs multiple parallel convolutional pathways to capture diverse features. In this project, we utilize InceptionV3 for its ability to extract rich features from retinal images, enhancing diabetic retinopathy classification accuracy.
- InceptionResNetV2: InceptionResNetV2 is an extension of the Inception architecture combined with residual connections. It combines the strengths of both architectures to achieve improved performance in image classification tasks. We incorporate InceptionResNetV2 in this project for its ability to capture intricate features in retinal images, contributing to enhanced diabetic retinopathy classification accuracy.
- Deep Residual Network: Deep Residual Network (ResNet) is a deep learning architecture featuring residual connections, enabling training of extremely deep neural networks. We use it in this project for its capability to extract hierarchical features from retinal images, aiding in diabetic retinopathy classification with improved accuracy.
- DenseNet201: DenseNet201 is a convolutional neural network architecture characterized by densely connected layers. It facilitates feature reuse and encourages feature propagation throughout the network. We employ DenseNet201 in this project for its ability to capture intricate patterns in retinal images, contributing to more accurate diabetic retinopathy classification.
- DenseNet121: DenseNet121 is a variant of the DenseNet architecture with 121 layers. It utilizes densely connected layers to facilitate feature reuse and propagation. We incorporate DenseNet121 in this project for its effectiveness in capturing detailed features from retinal images, improving diabetic retinopathy classification accuracy.
- Xception: Xception is a convolutional neural network architecture characterized by depthwise separable convolutions. It reduces computational complexity while maintaining performance. We utilize Xception in this project for its efficiency and effectiveness in extracting features from retinal images, enhancing diabetic retinopathy classification accuracy.

IV. Experimental Results

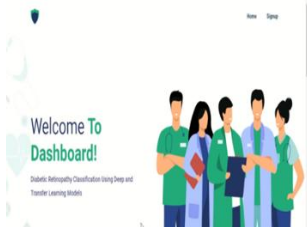

Fig 2 Home Page

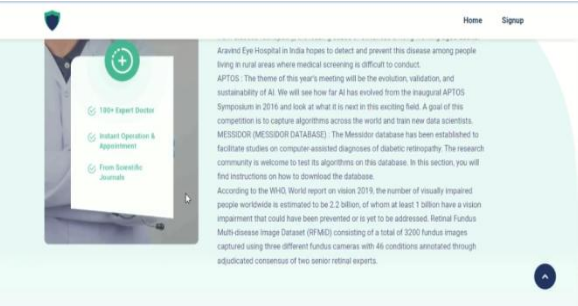

Fig 3 About Page

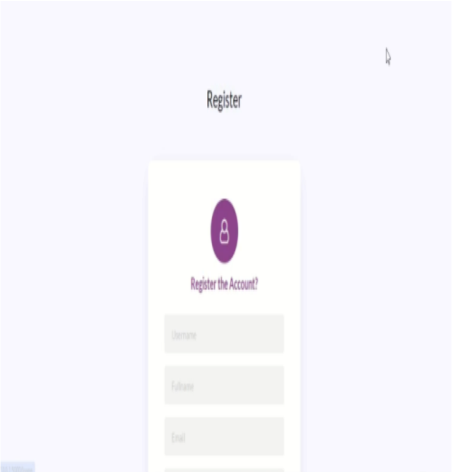

Fig 4 Registration Page

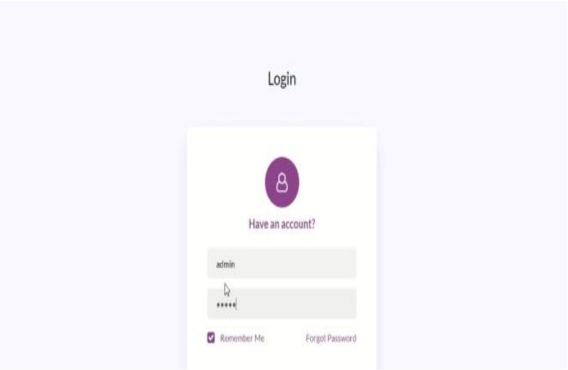

Fig 5 Login Page

Fig 6 Main Page

Fig 7 Accuracy Graph

Fig 8 Precision & Recall Graph

Fig 9 F1Score & FPR Graph

Fig 10 FNR Graph

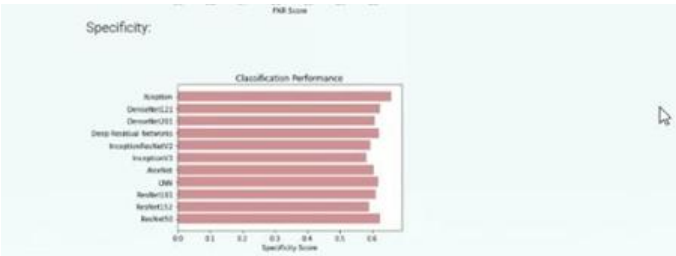

Fig 11 Sensitivity Graph

Fig 12 APTO Dataset Classification

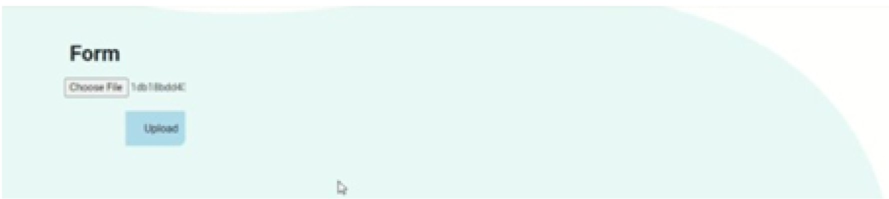

Fig 13 Upload Input Image

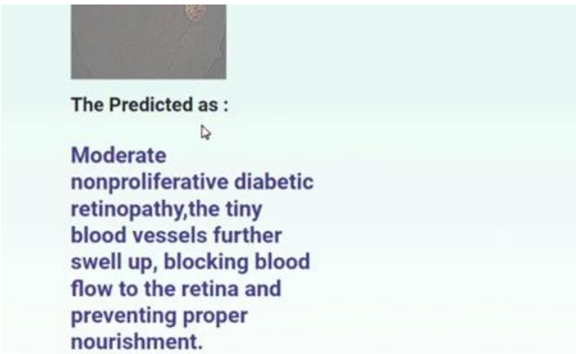

Fig 14 Predict Result

Fig 13 Messidor Dataset Classification

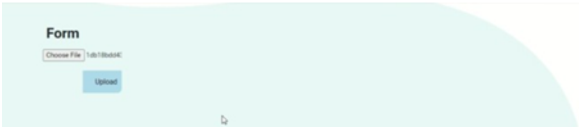

Fig 14 Upload Input Image

Fig 15 Final Outcome

Fig 16 Rfmid Dataset Classification

Fig 17 Upload Input Image

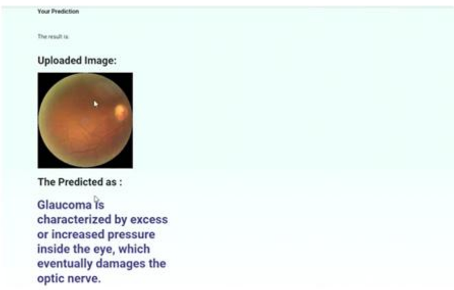

Fig 18 Predict Result For Given Input Image

Similarly, we can try other cases also to predict output based on given input image

V. Conclusion

In conclusion, this study explored the effectiveness of various deep learning architectures for diabetic retinopathy (DR) classification. Through rigorous experimentation, we evaluated the performance of ResNet50, ResNet152, ResNet101, CNN, AlexNet, InceptionV3, InceptionResNetV2, Deep Residual Network, DenseNet201, DenseNet121, and Xception on datasets including APTO, Messidor, and RFMiD. Our findings revealed that advanced architectures like ResNet152, InceptionV3, InceptionResNetV2, DenseNet201, and Xception achieved notable improvements in classification accuracy, with Xception notably surpassing 99% accuracy. These results signify the potential of leveraging state-of-the- art deep learning techniques for enhancing the diagnostic accuracy of DR, thus aiding in timely intervention and treatment planning to mitigate vision loss risks. However, challenges remain in ensuring scalability and robustness, especially when dealing with large and diverse datasets in real-world clinical settings.

VI. Future Scope

Future research could focus on optimizing model architectures, exploring ensemble techniques, and integrating additional clinical features for comprehensive DR diagnosis. Overall, this study contributes valuable insights into the application of deep learning in healthcare, particularly in the domain of diabetic retinopathy diagnosis, with implications for improving patient outcomes and reducing healthcare burdens.

References

[1] Pouya Saeedi, Inga Petersohn, Paraskevi Salpea, Belma Malanda, Suvi Karuranga, Nigel Unwin, Stephen Colagiuri, Leonor Guariguata, Ayesha A Motala, Katherine Ogurtsova, Et Al., "Global And Regional Diabetes Prevalence Estimates For 2019 And Projections For 2030 And 2045: Results From The International Diabetes Federation Diabetes Atlas," Diabetes Research And Clinical Practice, Vol. 157, Pp. 107843, 2019.

[2] Early Treatment Diabetic Retinopathy Study Research Group Et Al., "Grading Diabetic Retinopathy From Stereoscopic Color Fundus Photographs—An Extension Of The Modified Airlie House Classification: Etdrs Report Number 10," Ophthalmology, Vol. 98, No. 5, Pp. 786–806, 1991.

[3] Varun Gulshan, Lily Peng, Marc Coram, Martin C Stumpe, Derek Wu, Arunachalam Narayanaswamy, Subhashini Venugopalan, Kasumi Widner, Tom Madams, Jorge Cuadros, Et Al., "Development And Validation Of A Deep Learning Algorithm For Detection Of Diabetic Retinopathy In Retinal Fundus Photographs," Jama, Vol. 316, No. 22, Pp. 2402–2410, 2016.

[4] Maryam Badar, Muhammad Haris, And Anam Fatima, "Application Of Deep Learning For Retinal Image Analysis: A Review," Computer Science Review, Vol. 35, Pp. 100203, 2020.

[5] Daniel Shu Wei Ting, Carol Yim-Lui Cheung, Gilbert Lim, Gavin Siew Wei Tan, Nguyen D Quang, Alfred Gan, Haslina Hamzah, Renata Garcia-Franco, Ian Yew San Yeo, Shu Yen Lee, 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, Vol. 318, No. 22, Pp. 2211–2223, 2017.

[6] Jaakko Sahlsten, Joel Jaskari, Jyri Kivinen, Lauri Turunen, Esa Jaanio, Kustaa Hietala, And Kimmo Kaski, "Deep Learning Fundus Image Analysis For Diabetic Retinopathy And Macular Edema Grading," Scientific Reports, Vol. 9, No. 1, Pp. 1–11, 2019.

[7] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, And Dhruv Batra, "Gradcam: Visual Explanations From Deep Networks Via Gradientbased Localization," In Proceedings Of The IEEE International Conference On Computer Vision, 2017, Pp. 618–626.

[8] Mingxing Tan And Quoc Le, "Efficientnet: Rethinking Model Scaling For Convolutional Neural Networks," In International Conference On Machine Learning. PMLR, 2019, Pp. 6105– 6114.

[9] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, And Andrew Rabinovich, "Going Deeper With Convolutions," In Proceedings Of The IEEE Conference On Computer Vision And Pattern Recognition, 2015, Pp. 1–9.

[10] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, And Kilian Q Weinberger, "Densely Connected Convolutional Networks," In Proceedings Of The IEEE Conference On Computer Vision And Pattern Recognition, 2017, Pp. 4700–4708.

[11] Mohamed Chetoui And Moulay A Akhloufi, "Explainable Diabetic Retinopathy Using Efficientnet," In 2020 42nd Annual International Conference Of The IEEE Engineering In Medicine & Biology Society (EMBC). IEEE, 2020, Pp. 1966–1969.

[12] Xiaomeng Li, Xiaowei Hu, Lequan Yu, Lei Zhu, Chi-Wing Fu, And Pheng-Ann Heng, "Canet: Cross- Disease Attention Network For Joint Diabetic Retinopathy And Diabetic Macular Edema Grading," IEEE Transactions On Medical Imaging, Vol. 39, No. 5, Pp. 1483–1493, 2019.

[13] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, And Antonio Torralba, "Learning Deep Features For Discriminative Localization," In Proceedings Of The IEEE Conference On Computer Vision And Pattern Recognition, 2016, Pp. 2921–2929.

[14] Haofan Wang, Zifan Wang, Mengnan Du, Fan Yang, Zijian Zhang, Sirui Ding, Piotr Mardziel, And Xia Hu, "Score-Cam: Score-Weighted Visual Explanations For Convolutional Neural Networks," In Proceedings Of The IEEE/CVF Conference On Computer Vision And Pattern Recognition Workshops, 2020, Pp. 24–25.

[15] Harish Guruprasad Ramaswamy Et Al., "Ablation- Cam: Visual Explanations For Deep Convolutional Network Via Gradient-Free Localization," In Proceedings Of The IEEE/CVF Winter Conference On Applications Of Computer Vision, 2020, Pp. 983–991.

[16] Ahmed Salama, Noha Adly, And Marwan Torki, "Ablationcam++: Grouped Recursive Visual Explanations For Deep Convolutional Networks," In 2022 IEEE International Conference On Image Processing (ICIP). IEEE, 2022, Pp. 2011–2015.

[17] Nobuyuki Otsu, "A Threshold Selection Method From Gray-Level Histograms," IEEE Transactions On Systems, Man, And Cybernetics, Vol. 9, No. 1, Pp. 62– 66, 1979.

[18] Y. Zhou, B. Wang, L. Huang, S. Cui, And L. Shao, "A Benchmark For Studying Diabetic Retinopathy: Segmentation, Grading, And Transferability," IEEE Transactions On Medical Imaging, Vol. 40, No. 3, Pp. 818–828, 2021.

[19] "Kaggle. Diabetic Retinopathy Detection (Data)," Https://Www.Kaggle.Com/C/Diabetic- Retinopathydetection/Data, 2015.