

INTEGRATIVE DETECTION OF RETINAL DETACHMENT WITH ALEXNET AND HEAT MAPS VISUALIZATION

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Abstract: This study at investigates the application of the AlexNet convolutional neural network with heatmap visualizations for detecting retinal detachment (RD). Using a dataset of optical coherence tomography (OCT) pix classified into four categories—choroidal neovascularization (CNV), diabetic macular edema (DME), DRUSEN, and NORMAL—the version done good consequences. AlexNet's deep mastering skills yielded a one hundred% accuracy rate in classifying those conditions. Grad-CAM heatmap visualizations furnished insights into the model's decision-making process through highlighting important picture regions influencing each prediction. This approach no longer best more suitable diagnostic accuracy however additionally progressed interpretability, making the model's outputs extra transparent and clinically applicable.

INTRODUCTION

The eye is a vital organ required for everyday human activity; it is a complex organ that requires multiple essential elements to operate. The eyes are the primary sensory organ for vision, allowing people to see their environment and process information. One element of the eye that is essential to vision is the retina. As such, the retina is considered an important component of the eye and plays a significant role in distinguishing between various objects [9]. The retinal layers detach from their original place due to a serious medical condition called retinal detachment (RD). It's a severe visual issue that requires immediate attention to prevent permanent eyesight loss. All ages are increasingly experiencing retinal-based disorders, which impair vision clarity by causing fuzzy images and even total blindness [15]. RD can happen through a variety of mechanisms, whatever the mechanism, the accumulation of fluid under the retina is a common feature of all kinds of RD [5]. RD diagnosis made early and accurately is essential for prompt intervention and improved patient results [10]. Even though most instances are asymptomatic in the course of the initial tiers of the disorder, its early detection and treatment can help to postpone or avoid a terrible evolution [17]. When a young patient provides with abrupt unilateral imaginative and prescient loss, there are numerous in all likelihood reasons, such as optic neuropathy or retinopathy [12]. It is important to remember that there are several RD types based on the reasons or the degree of detachment. Diabetic macular edema (DME) is marked by fluid

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accumulation in the inner and outer plexiform layers, leading to increased retinal thickness. Choroidal neovascularization (CNV) in exudative age-related macular degeneration is characterized by abnormal blood vessel growth from the choroid into the neurosensory retina, DRUSEN which are small yellow deposits of lipids beneath the retina and Bruch's membrane.

Typically, there are 12 instances of RD consistent with 100,000 human beings every year [4]. Various imaging techniques, such as fundus photography, Optical Coherence tomography (OCT), and B-scan ultrasonography, provide detailed information on the retinal architecture and help clinicians identify the type and severity of RD [8]. Optical coherence tomography angiography (OCT-A) gives excessive-decision images of retinal anatomy and microvasculature through some modalities permitting signal penetration to the choroid [2]. The training dataset, made up of OCT images. The foundation of modern medicine is made up of indicators that are invisible to physicians but that can be found by applying deep learning (DL) and big data techniques. Because this type of technology is far more capable of analyzing and comprehending vast amounts of data than humans are, researchers in the medical and healthcare fields are growing increasingly interested in DL because it can increase the precision of medical applications by using medical data [18]. Deep learning algorithms have significantly impacted the medical field, especially in diagnostic imaging. AlexNet, a pioneering convolutional neural network, has demonstrated exceptional performance in analyzing medical images, identifying patterns, and classifying conditions with high accuracy. Supplementing AlexNet, heatmap visualization techniques for instance Grad-CAM improve the interpretability of model estimates. These imaginings highlight critical regions within images, serving clinicians recognize and trust the model's results. Together, AlexNet and heatmap visualizations recover diagnostic accuracy, provision early disease discovery, and ultimately augment patient care. This study uses AlexNet and Grad-CAM heatmap visualizations to develop the accuracy and interpretability of retinal detachment detection in medical imaging. Much less exertion and time might be required with automated analysis and prognosis [16].

RELATED WORK

In 2019, Li, et al. [13] A 4-class classification problematic was proposed to automatically identify choroidal neovascularization (CNV), diabetic macular edema (DME), DRUSEN, and NORMAL in optical coherence tomography (OCT) pictures. The collective of four classification model instances was working by the proposed classification algorithm to distinguish retinal OCT images. Each classification model example was built using an improved Residual Neural Network (ResNet50). The recommended methodology attained a classification accuracy of 0.973, a sensitivity of 0.963, and a specificity of 0.985 at the B-scan level, thereby achieving a performance that matches or exceeds that of ophthalmologists possessing substantial clinical expertise. A total of 21,357 retinal OCT imageries were collected from 2,796 adult patients between 2014 and 2019.

In 2019, Shanthi and Sabeenian [20] examined the use of a modified AlexNet building for the categorization of diabetic retinopathy (DR) images. The study got notable classification accuracies of 96.6% for healthy images and 96.2%, 95.6%, and 96.6% for phases 1, 2, and 3 of DR, correspondingly, using the Messidor database, which includes retinal images used for benchmarking DR classification algorithms. This study highlights the possibility for early discovery and therapy to evade vision

loss by representing how well Convolutional Neural Networks CNNs distinguish and classify diverse degrees of DR severity. Their model's outstanding performance displays how sophisticated neural network topologies have a big influence on medical image processing.

In 2021, Parra-Mora, et al. [17] projected an automatic approach for distinguishing the Epiretinal membrane (ERM) in OCT retinal imagery, an illness of the eyes identified as ERM affects 7% of people universally. Using transfer learning, four popular CNN architectures (AlexNet, SqueezeNet, ResNet, and VGGNet) were modified and refined using a confidential dataset, with a mean accuracy of 99.7%, a mean sensitivity of 99.47%, and mean specificity of 99.93%, ResNet was the best-performing network.

In 2022, Zhou, et al. [22] employed deep learning techniques to identify recurrent RD utilizing Ultra-Widefield Fundus images (UWF). The deep learning system with ResNet-50 and Inception-ResNet-V2 was developed and internally validated to identify recurrent RD and retina reattachment after surgery. The dataset used 554 UWF fundus images from 173 patients diagnosed with RD were utilized to develop the deep learning (DL) system. The deep learning system demonstrated area under the curve (AUC) values of 0.912. Specificity, sensitivity, AUC, and accuracy obtained using ResNet-50 are 92.9%, 84%, 0.935, and 91.2, respectively. Moreover, Inception-ResNet yields specificity, sensitivity, accuracy, and AUC values of 87.8%–89%, 0.944, and 90.6, in that order.

In 2023, Brehar, et al. [3] proposed a hybrid approach that combines deep learning-based retinal layer segmentation with feature-based image classification to identify specific biomarkers for Age-related Macular Degeneration (AMD). The dataset used is the Annotated Retina OCT Images, which contains 1,136 images from 24 patients with annotations for biomarkers and retinal layers in patients with AMD conditions. The paper focused on the segmentation of biomarkers for AMD from retinal OCT images. The article introduces a variety of techniques for segmenting OCT images, which are capable of accurately detecting the different layers of the retina and any fluids that may appear in the image. In cases where the fluids are difficult to identify, a classification method based on features was employed. This approach combines textural characteristics with machine learning, resulting in a 90% accurate classification between the fluids and the retinal layers in which they are located.

ALEXNET NETWORK

In 2012, AlexNet emerged as the first deep learning architecture to win the ImageNet challenge, winning by a wide margin of about 11.3%, GPU training was utilized by the AlexNet team to increase productivity, prior to 2012, the image classification model failure rate was approximately 25%; however, AlexNet remarkably exceeded that error rate by 15.3% in the 2012 ImageNet challenge. Its structure is comparable to LeNet-5's, but it has more layers and filters, which produce more learning variables and a better outcome overall, CNNs like AlexNet are cutting edge and created especially for image categorization applications. In image classification and object identification tasks, AlexNet has shown itself to be the most advanced architecture [21]. It made headlines in the deep learning sector in 2012 when it emerged victorious in the ImageNet Large Scale Visual Recognition Challenge. The main building blocks of AlexNet are convolutional layers, max-pooling layers, normalizing layers, and fully connected layers. It uses dropout regularization and the Rectified Linear Unit (ReLU) activation function to improve

performance. TensorFlow was utilized to produce AlexNet. The situations of the RD detection challenge were taken into consideration when choosing exact setups and hyperparameters. The AlexNet network was trained for the job of RD discovery using a diverse dataset containing retinal imageries annotated with ground truth tags. The dataset involved of 569 imageries, with each image characterized as either showing a healthy retina or viewing signs of detachment. Before to training, collective data preprocessing was conducted to standardize the input imageries, containing the size changing to a uniform resolution and regularizing pixel intensities. Data augmentation actions such as random rotating, horizontal flipping, and zooming in were also applied to augment the images and enlarge the model's generalization capability. AlexNet able to generate a 4096-dimensional feature vector immediately prior to the output layer, which covers the activations of the unseen layer, with 650,000 neurons and 60 million parameters, AlexNet is a huge constructing in and of itself [14]. Stochastic gradient descent (SGD) was utilized as the optimization algorithm, with a learning degree of 0.001. A batch size of 32 was applied to make balance computational efficacy and model convergence. shape 1 below explain the structure of the Alexnet.

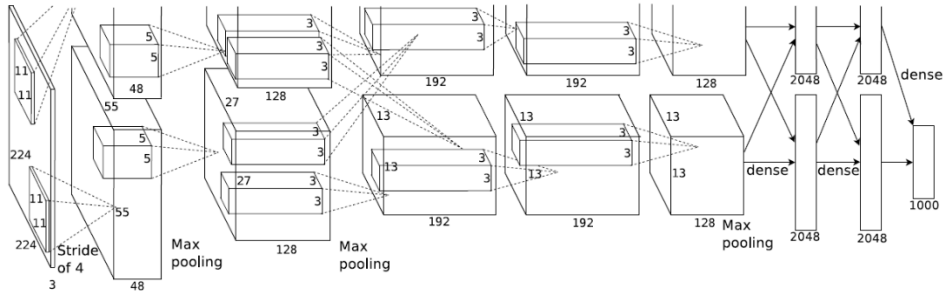


Figure 1: Alexnet Architecture [11].

HEATMAP VISUALIZATION OF RD

Heatmap imaging is a crucial gizmo in the fields of computer vision plus deep learning, serving in the Comprehension of Convolutional Neural Networks' (CNNs) Judgment-making processes. Usually used for visualizing statistical data in a matrix-like format, heatmaps give forms among rows and columns. Complicated heatmaps are particularly operative for identifying contacts between numerous data sources [7]. One of the common ways for making heatmaps is Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM makes heatmaps that focus on important features of the input data [1]. In this work, Grad-CAM was utilized to visualize zones of attention in imageries classified by a pre-trained CNN, precisely the ResNet-50 model. This Strategy offers insights into the parts of an image that the CNN attentions on during the prediction procedure. The Grad-CAM heatmaps obviously show which zones the model considered most noteworthy for Categorization. This visualization rallies the transparency and comprehensibility of the AI system by recognizing key areas in the images and analyzing the model's presentation. In our analysis, Grad-CAM was Utilized to images classified by the ResNet-50 model, and trained on the ImageNet imageries. By focusing and coloring the areas of attention, this heatmap helps us realize the model's focus during Categorization. Grad-CAM uses slope information flowing into the CNN's last

convolutional layer to assign relevance values to each neuron for a specific judgment [19]. Heatmap visualizations afford some benefits beyond basic visualization. They allow a detailed investigation of the CNN's inner workings by showing which slices of an image contribute most to the last Categorization. For example, in medical image examination, a heatmap can highlight parts of a scan most indicative of a specific sickness, assisting in diagnosis and cure preparation. The visual representation of data through heatmaps can reveal hidden structures and patterns that might not be promptly clear through raw data alone. Moreover, heatmap imaginings like Grad-CAM are crucial for debugging and supporting model performance. By identifying the parts of the image which the model highlights, researchers and specialists can fine-tune the network, address biases, and assurance that the model's judgments are based on connected features rather than unrelated background elements. This procedure growths the model's Understandability and reliability, which is mainly significant in sensitive fields such as medical image examination. The figure 2 below explains the use of Grad-CAM for visualizing zones of attention in images categorized by the ResNet-50 model. The primary row shows an image categorized as a "Dog," with the identical Grad-CAM heatmap on the right. The heatmap highlights the dog's skull, representative that this area was most powerful in the model's judgment. Likewise, the second row represents an image labeled as a "Cat," with its associated Grad-CAM heatmap. In this situation, the heatmap highlights the part around the cat, giving the model's focus during Categorization. These imaginings are instrumental in understanding which features the model deems significant, thereby enhancing the transparency and Understandability of the CNN's decision-making process. By exploring these heatmaps, researchers can confirm that the model's guesses are based on relevant features, which is important for Advancing model accuracy and reliability.

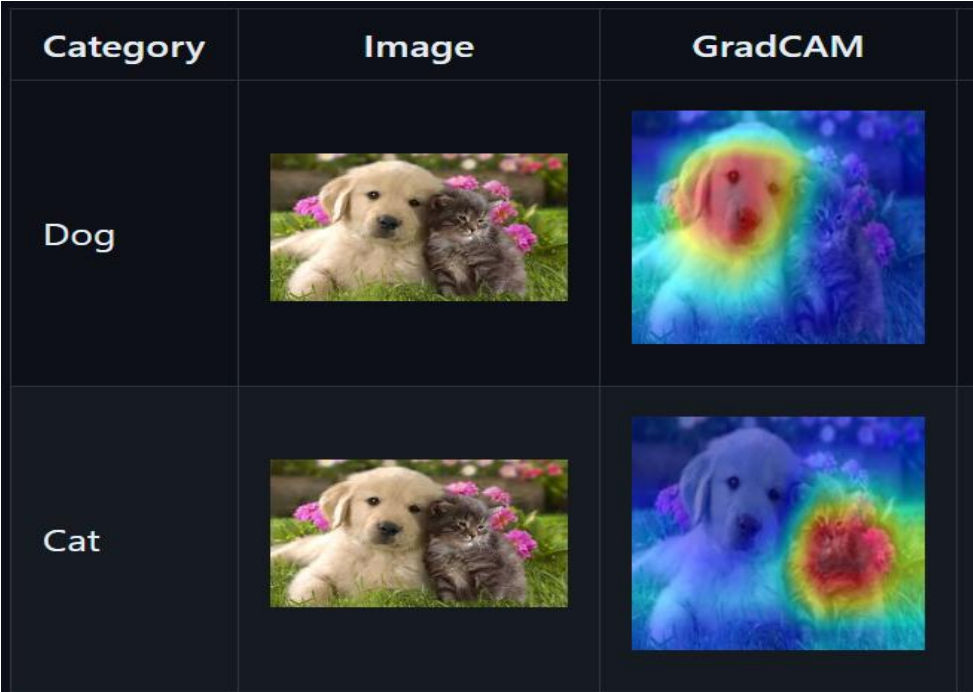


Figure 2: Exploring Dog and Cat Recognizing with Heatmaps [6].

THE PROPOSED SYSTEM

In this work, the performance of AlexNet was created in noticing RD from retinal imageries. Moreover, heatmap visualisation is utilized to highlight the parts of interest identified by these algorithms, Supplying an intuitive realization of their decision-making processes. This paper goals to assess the efficacy of these algorithms and the added value of heatmap imaginings in the context of RD. These imageries were marked to recognize areas of RD, supplying a reliable ground truth for training and evaluating the algorithms.

Alex-Net

The workflow of the deep learning model development process for categorizing RD into four sorts (CNV, DME, NORMAL, and DRUSEN) is demonstrated by the figure 3. The process is happening with the dataset import, which contains Marked imageries from these categories. The later step includes the preprocessing of imageries, primarily focusing on resizing them to a uniform dimension (245x245). Next preprocessing, the dataset is divided into three divisions: training (80%), validation (15%), and test (5%). The model construction is defined using the AlexNet framework, which includes multiple convolutional layers with max-pooling, followed by dense layers and dropout for organizing. During the training process, the training and validation sets are used, with early stopping implemented through a callback function if the accuracy threshold of 99.9% is attained. Upon completion of training, the model undergoes evaluation using the test set to define its performance. Later, the evaluation results, encompassing loss and accuracy curves, are examined to assess the model's effectiveness. This organized approach ensures the development of a robust and efficient pipeline for the making of a deep learning model for medical image classification.

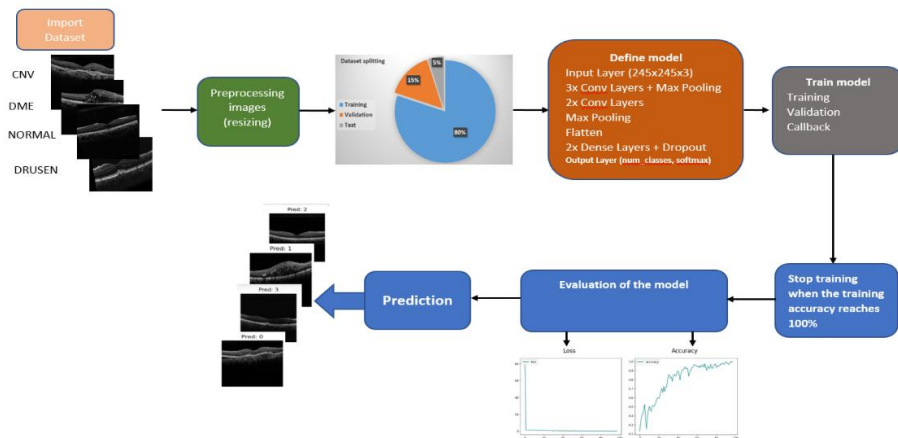


Figure 3: The Workflow of the Alexnet Model.

Heatmap Visualization

The block diagram presented in figure 4 below provides a complete overview of the workflow for generating Grad-CAM visualizations in the situation of medical image classification. The process begins with importing a labeled dataset of medical

imageries categorized into CNV, DME, NORMAL, and DRUSEN. These imageries are preprocessed by resizing them to 224x224 pixels, changing them to arrays, increasing their dimensions, and applying ImageNet preprocessing techniques. A pre-trained ResNet 50 model, using ImageNet weights, is then loaded to help as the CNN framework for feature extraction. Grad-CAM is set with the pre-trained model to recognize the target convolutional layer for heatmap generation. The heatmap, which highlights areas of interest in the imageries, is computed and then overlaid on the original images to make a visual illustration of the model's focus regions. The processed images are saved and optionally presented for visual assessment. This organized pipeline ensures robust and interpretable Grad-CAM visualizations, helping in the effective classification and examination of medical images.

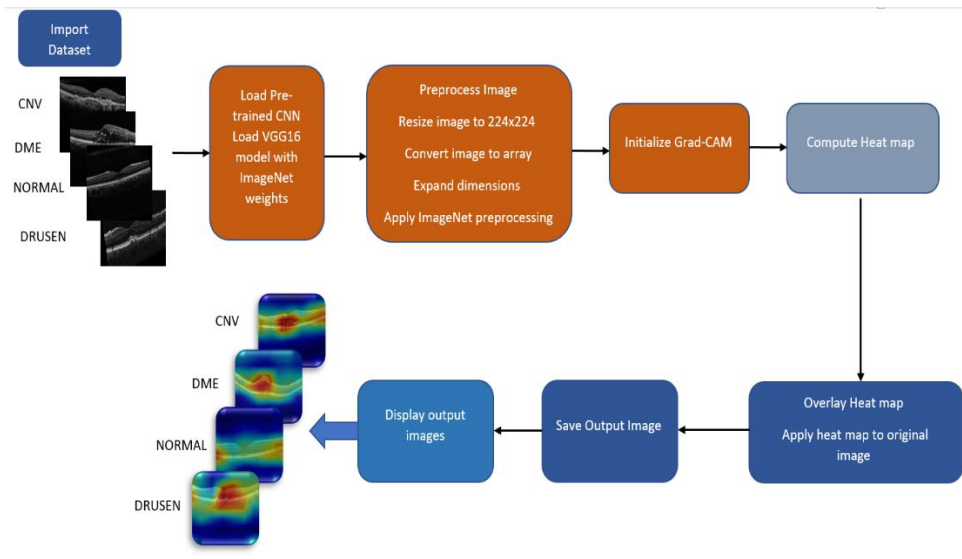


Figure 4: Complete Heatmap Visualization Procedure for RD Analysis.

Dataset

The datasets used in this work contain 569 images for four classes (CNV, DME, DRUSEN, and NORMAL), got from Al-Rabee Hospital, Al-Sukar Quarter, Mosul, Iraq. After applying data augmentation methods, the number of imageries increased to 925, improving the training dataset's variety and improving the model's robustness. The dataset contains images from older adult males and females with DRUSEN, persons of all ages and both genders with DME, older adults of both genders with CNV, and individuals of all ages and both genders with NORMAL retinal state. Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen are retinal detachment conditions. CNV and Drusen are more common in older adults, usually over 50 and 60 years old respectively, without notable gender differences. DME, linked to diabetes, affects adults across various age groups but is more prevalent among middle-aged and older individuals, without any gender-specific patterns. This diverse demographic representation ensures comprehensive model training across different age groups and both genders. the images size 1024x512, to standardize the input data for the deep learning network, all images were resized to 640x640 pixels. This resizing ensures consistent input

dimensions, which is crucial for the effective training CNNs. Figure 5 shows the samples for four classes of the RD dataset.

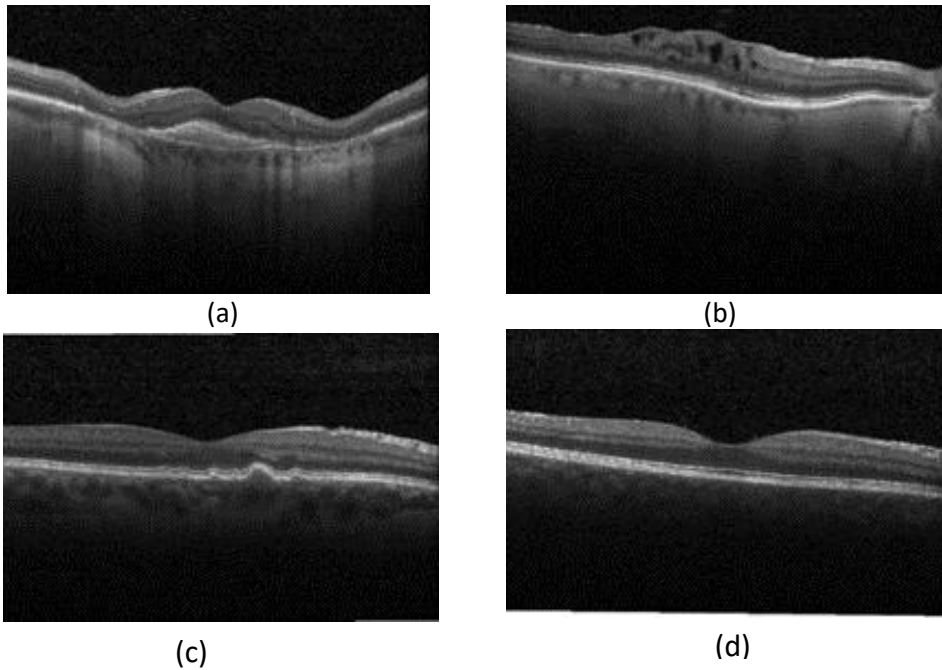


Figure 5: Samples for four Classes of the RD Dataset.

- (a) Choroidal neovascularization (CNV),
- (b) Diabetic macular oedema (DME),
- (c) DRUSEN and (d) Normal case

Dataset Splitting

To ensure the models' reliability and resilience, the dataset was divided into training, validation, and test sets, with the distribution as follows: the training set included 740 images, comprising 80% of the total images, the validation set consisted of 139 images, making up 15% of the total images, and the test set contained 46 images, accounting for 5% of the total images, as Figure 6 below illustrates.

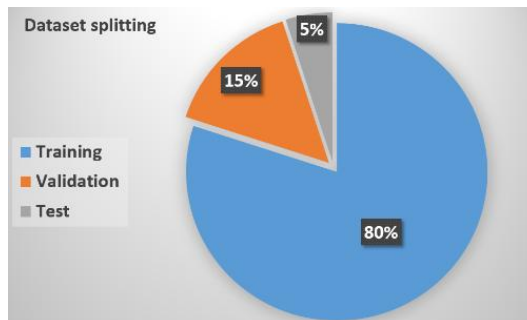


Figure 6: Splitting Percentages for the Dataset.

RESULT

In this study, we leveraged cutting-edge deep learning models and visualization techniques to improve the detection and analysis of RD. AlexNet was employed to classify medical images into categories such as normal, diabetic retinopathy, macular degeneration, and RD. To enhance the interpretability of the model's decision-making processes, we implemented Gradient-weighted Class Activation Mapping (Grad-CAM), which produces heatmaps that highlight the crucial regions of the images influencing the model's classifications. This complete approach confirms high accuracy, speed, and clarity, contribution a robust solution for retinal image examination.

Alexnet Training Results

The training log offers valuable insights into the model's presentation above 150 epochs, revealing key trends and results. Initially, the model displays low accuracy, about 30%, along with high loss, which is expected as the model starts to learn from the data. As the epochs progress, both training and validation accuracies recover steadily. By epoch 21, the validation accuracy reaches roughly 76%, representing the model's improving generalization ability. Notable increases in validation accuracy are noticed as training continues: about 88% by epoch 39, 94% by epoch 53, and 95% by epoch 62. After about 50 epochs, the validation accuracy regularly reaches high levels, nearing or achieving 95%.

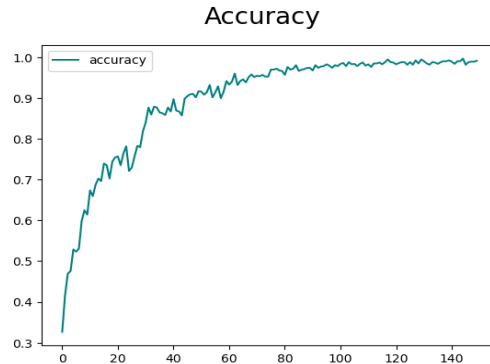


Figure 7: The Accuracy Graph of the Alexnet Model.

Concomitantly, loss values reduced significantly, indicating that the model's expectations are becoming more exact and confident. While achieving high validation accuracy consistently is hopeful, it may also suggest potential overfitting, particularly if the training accuracy is likewise high. It is crucial to monitor validation loss to ensure the model is not merely memorizing the training data. A low validation loss along with high accuracy is a strong indicator of the model's performance. Balancing accuracy and loss is essential: high accuracy on the validation set demonstrates good generalization, with 76-95% accuracy suggesting strong performance on unseen data; lower loss values indicate that predictions are closely aligned with actual values, and monitoring both training and validation loss helps detect overfitting, where the model might excel on training data but underperform on validation data. In conclusion, the training log shows that the model achieves high performance, with accuracy often

nearing 95%. This indicates a well-trained model. The graph depicts in Figure 7 the accuracy development of the AlexNet model across its training phase, which was initially set to run for 150 epochs. Initially, the model demonstrates a low accuracy of approximately 30%, which is typical at the start of training. As training progresses, accuracy shows a marked improvement, reaching around 76% by the 21st epoch. The upward trend continues with further significant gains: approximately 88% by epoch 39, 94% by epoch 53, and 95% by epoch 62. Notably, the accuracy reaches a high score at epoch 95.

Figure 8 illustrates the loss trajectory of the AlexNet model over 45 epochs during its training phase. Although the training was initially scheduled for 100 epochs. At the start of training, the model's loss is notably high, around 40, which is typical for the initial stages. However, the loss rapidly decreases within the first few epochs, signifying the model's swift adaptation to the training data. By the tenth epoch, the loss has significantly dropped to nearly 5. Following this, the loss continues to decline at a slower rate, stabilizing at a low level for the remainder of the training period. By epoch 45, the loss reaches a minimal and nearly constant value, indicating that the model has effectively learned and optimized its parameters. This plot efficiently showcases the model's quick convergence and its efficient learning procedure from the training dataset.

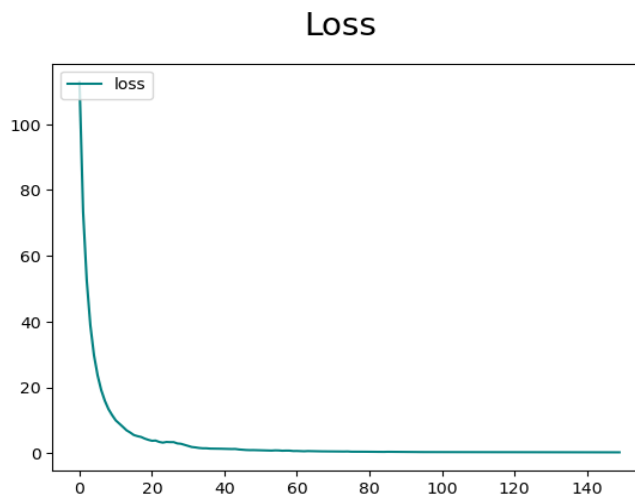


Figure 8: The Loss Graph of the Alexnet Model.

The confusion matrix showed in Figure 9 explains the performance of our AlexNet model in categorizing retinal images into four categories: NORMAL, DME, DRUSEN, and CNV. The matrix detects that our model attained a perfect classification accuracy for all classes, with no misclassifications detected. Exactly, all 13 images labeled as NORMAL were properly classified as NORMAL, all 18 images of DME were precisely identified as DME, all 11 imageries of DRUSEN were properly classified as DRUSEN, and all 22 imageries of CNV were accurately recognized as CNV. This exceptional performance is indicative of the model's strong capability to recognize between the different retinal situations. The overall categorical accuracy attained was 1.0, emphasizing the efficacy of our approach in RD detection utilizing deep learning algorithms.

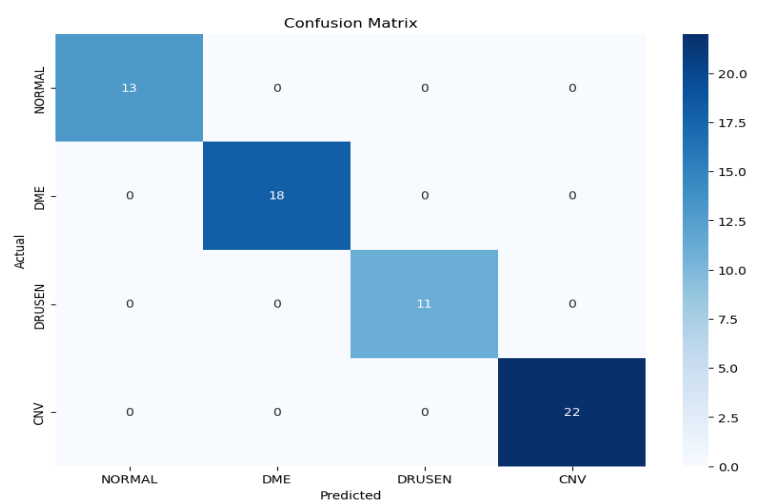


Figure 9: Confusion Matrix of Alexnet Model.

A confusion matrix calculates the performance of a organization model by comparing expected and actual labels. It includes False Negatives (FN), True Positives (TP), True Negatives (TN), and False Positives (FP).

Heatmap Visualization

Gradient-weighted Class Activation Mapping, or Grad-CAM, is a influential technique that may be utilized to visualize the important regions that a deep learning model concentrates on while detecting diverse eye problems. This technology is utilized to retinal images. By highlighting the parts that have the major impact on the model's predictions, this technique provides important insights into how the model creates decisions. Different patterns connected with each disease are showed in the heatmaps made for each class: DME (Diabetic Macular Edema), CNV (Choroidal Neovascularization), DRUSEN, and NORMAL. The lack of noticeable red or yellow patches on the heatmap of normal retinal images indicates low activation. This indicates that the model discovers nothing unusual, indicating that the image is typical. The nonappearance of diseased characteristics in the retinal layers is revealed in the lack of bright colors. The heatmaps display dark red and yellow spots in images classed as DME, indicating the regions where fluid buildup and retinal thickening happen. Given that the model focuses on the enflamed areas of the retina, these visual signs advise the being of diabetic macular edema. The heatmaps Present noticeable portions with vibrant colour patches that represent drusen deposits in DRUSEN situations. These deposits, which are shaped from proteins besides lipids and are situated under the retina, are essential for the model to Differentiate this situation. The heatmap's highlighted parts show the places where the model finds these pathological changes. Heatmaps with strong highlights around newly formed aberrant blood vessels are presented in the CNV images. The model noticed these neovascular alterations, as showed by the bright red and yellow patches. To highlight particular regions of attention within the retinal layers, we show heatmap representations of Optical Coherence Tomography (OCT) imageries in this work. The areas with diverse intensities are clearly depicted in the heatmaps, highlighting places that might be indicative of illnesses or other noteworthy traits.

These imaginings allow for a more thorough analysis of the retinal anatomy, which is crucial for better understanding and analyzing retinal diseases. The above-mentioned composite picture displays several retinal slices with associated heatmap overlays: Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), Drusen, and a Normal retina. and the Figure 10 below displays the result of heatmap visualization for the four cases of RD (CNV, DME, DRUSEN, NORMAL)

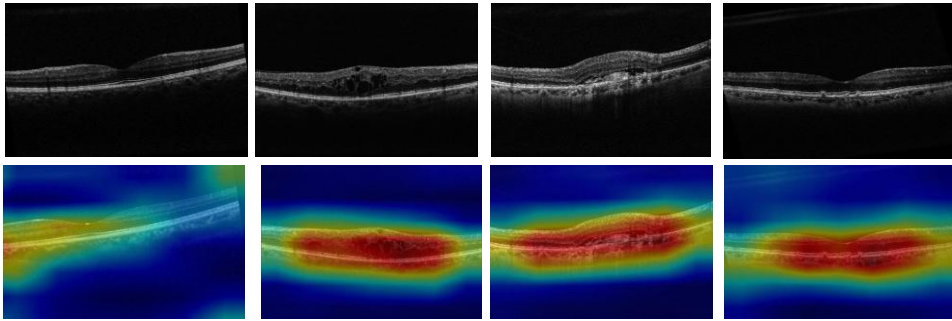


Figure 10: Heatmap Visualizations of Retinal Detachment for Different Classes (A) NORMAL, (B) DME, (C) CNV, (D) DRUSEN.

CONCLUSION

AlexNet and Grad-CAM heatmap visualizations yielded widespread results in the detection and category of retinal detachment. The version's great accuracy in differentiating between CNV, DME, DRUSEN, and NORMAL retinal conditions demonstrates its robustness and reliability. Grad-CAM visualizations efficiently highlighted the areas that contributed to the model's predictions, enhancing the transparency and trustworthiness of the diagnostic method. These outcomes underscore the ability of mixing superior neural networks with visualization techniques to help clinical prognosis. The achievement of this method shows promising future instructions for enhancing early prognosis and treatment making plans in ophthalmology, with the potential for integration of other neural network architectures and visualization methods to further beautify diagnostic accuracy and interpretability.

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