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DETECTION OF DIABETIC EYE DISEASE FROMRETINAL IMAGES USING A DEEP LEARNING BASED ON CENTERNET AND DENSENET MODEL

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Abstract: Diabetic patients are prone to eye disease called Diabetic Retinopathy that affects blood vessels of the retina of diabetic patients. Diabetic retinopathy stands as a foremost cause of vision impairment globally. The earliest diabetes-related changes in theretina are often imperceptible and have minimum impact in the vision and thus approximately one third of the diabetic patients haveDR but show no symptoms, leading to the progression of the disease untreated. The complexity of screening methodologies for diabetic eye diseases and the shortage of adequately trained personnel render the development of effective screening-oriented treatments a financially burdensome endeavor. Our proposed framework demonstrates proficiency in accurately localizing and categorizing disease lesions within retinal images thus facilitating automated detection and recognition of diabetic retinopathy, thusenabling early detection for efficient treatment with low cost and high accuracy.

Index Terms – Diabetic Eye Disease, Diabetic Retinopathy, Deep Learning, Retinal Disease.

I. INTRODUCTION

Diabetic retinopathy (DR) is a serious complication of diabetes that affects the eyes, potentially leading to vision impairment or blindness if left untreated. Early detection of DR is crucial for timely intervention and management to prevent vision loss in diabetic patients. Traditional methods of DR diagnosis involve manual screening by ophthalmologists, which can be time- consuming and resource-intensive. However, recent advancements in deep learning have paved the way for automated and efficient DR detection systems.

In this journal, we present a novel approach using a deep learning-based CenterNet model for the detection of diabetic retinopathy from retinal images. Our methodology harnesses the power of convolutional neural networks (CNNs) to automatically identify signs of DR with high accuracy and reliability. By leveraging a CenterNet architecture, we aim to improve both the efficiency and effectiveness of DR screening, enabling early intervention and reducing the burden on healthcare systems.

Diabetic retinopathy progresses through several stages, each characterized by distinct changes in the retina:it is illustratred in figure 1 **Mild Non proliferative Retinopathy (NPDR):** In the early stage, small areas of balloon-like swelling (microaneurysms) may appear in the retinal blood vessels. These microaneurysms can leak fluid into the retina.

Moderate NPDR: As the disease progresses, blood vessels that nourish the retina may swell and distort. This stage is characterized by the development of more severe microaneurysms, as well as the presence of small amounts of bleeding in the retina.

Severe NPDR: In this stage, many blood vessels become blocked, depriving areas of the retina of their blood supply. The retina responds by growing new blood vessels, a process called neovascularization.

Proliferative Diabetic Retinopathy (PDR): This is the advanced stage of diabetic retinopathy. At this point, the growth of new blood vessels can cause serious vision problems. These new blood vessels are fragile and can bleed into the vitreous (the gel-like fluid that fills the eye).

The CenterNet model employed in our study is designed to identify specific features associated with each stage of diabetic retinopathy. By accurately localizing and classifying abnormalities such as microaneurysms, hemorrhages, and neovascularization, our deep learning approach can assist clinicians in diagnosing and monitoring the progression of DR.

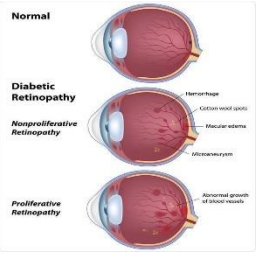

Figure 1: Different stages of Diabetic Retinopathy

In summary, the integration of deep learning techniques, particularly the CenterNet model, represents a promising advancement in the field of diabetic retinopathy detection. By automating and optimizing the screening process, our approach has the potential to enhance clinical outcomes and facilitate timely interventions for diabetic patients at risk of vision loss due to DR.

II. LITERATURE SURVEY

[1] "Classification of diabetic retinopathy and diabetic macular edema", The purpose of the current paper is to review the classification of DR with a special emphasis on the International Clinical Disease Severity Scale for DR. This new classification is simple to use,easy to remember and based on scientific evidence.

[2] "Grader variability and the importance of reference standards for evaluating machine", Images were each graded by the algorithm,
U.S. board-certified ophthalmologists, and retinal specialists.

[3] "Uncertainty aware deep learning-based diabetic retinopathy grading in eye fundus images", The low a Detection Program (IDP)– without deep learning components on the same available set of fundus images and reported consensus.

[4] "Deep image mining for diabetic retinopathy screening", A generalization of the backpropagation method is proposed in order totrain Conv Nets that produce high-quality heatmaps.

[5] "Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning", Implementing deep-learning enhanced algorithm for automated detection of diabetic retinopathy (DR).

III. METHODOLOGY

Our proposed method employs a comprehensive methodology combining the strengths of the DenseNet-100 architecture with the CenterNet model for the detection and classification of diabetic retinopathy stages from retinal images. The step-by-step approach encompasses data preprocessing, model development, training, and evaluation.

1. Data Preprocessing:

We begin by collecting a diverse and representative dataset of retinal images containing various stages of diabetic retinopathy, including mild non proliferative retinopathy (NPDR), moderate NPDR, severe NPDR, and proliferative diabetic retinopathy (PDR). Each image is annotated with bounding boxes and corresponding class labels indicating the specific stage of DR present.

2. Feature Extraction with DenseNet-100:

To extract meaningful features from the retinal images, we utilize the DenseNet-100 architecture, renowned for its denseconnectivity patterns and efficient feature propagation. DenseNet-100 is employed as a feature extractor to capture rich representations of the retinal structures at different scales and complexities.

3. Integration with CenterNet Model:

The extracted features from DenseNet-100 are then integrated into the CenterNet model, which serves as the backbone for both localization and classification tasks. The CenterNet architecture is chosen due to its effectiveness in simultaneous object detection and classification, making it ideal for identifying and categorizing specific DR-related abnormalities within retinal images.

4. **Model Development and Training:**
We develop a custom CenterNet-based framework tailored to the task of diabetic retinopathy detection. The model architecture incorporates the DenseNet-100 backbone followed by additional layers for heatmap generation, bounding box regression, and classification of DR stages. We use transfer learning by initializing the DenseNet-100 with pre-trained weights on a large-scale image dataset, fine-tuning its parameters on our retinal image dataset to adapt it for DR detection.

5. **Evaluation and Validation:**
We evaluate the trained model using standard metrics such as accuracy, precision, recall across different DR stages. A separate validation set is used to assess the generalization performance of the model and detect potential overfitting issues. Qualitative analysis is also conducted by visualizing model predictions overlaid on test images.Evaluation is illustrated by figure 2

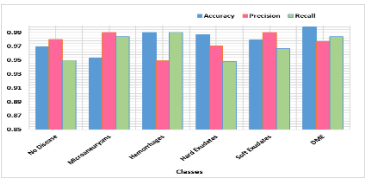

Figure 2: Evaluation and validation

In summary, our methodology leverages the synergy between DenseNet-100 and CenterNet, enabling accurate localization and classification of diabetic retinopathy stages from retinal images. The integration of deep learning techniques and transfer learning ensures robust performance and scalability, with potential implications for improving diagnostic workflows and patient outcomes in ophthalmology.

IV. RESEARCH METHODOLOGY

Population and Sample

The study centers on individuals been diagnosed with diabetes mellitus, specifically those at risk to develop diabetic retinopathy (DR). With millions affected worldwide by diabetes and its prevalence increasing, there's an acknowledged connection between diabetes and DR. The study incorporates individuals with both type 1 and type 2 diabetes, spanning various age groups, ethnicities, and geographical regions. In terms of sample selection, inclusion criteria include individuals been diagnosed with type 1 or type 2 diabetes within a specified age range, ensuring the availability of retinal images for analysis. Exclusion criteria involve individuals with pre-existing retinal diseases other than diabetic retinopathy and poor quality retinal images unsuitable for analysis. Convenience sampling will be employed; recruiting participants from diabetic clinics, hospitals, or healthcare facilities where retinal imaging services are available. The determination of the sample size will be based on statistical considerations, like the desired level of significance, power of the study, and anticipated effect size. Insights from previous studies on diabetic retinopathy detection using deep learning methods will help to inform the sample size determination. Ethical considerations are paramount. Informed consent will be obtained from all participants, providing detailed information about the study objectives, procedures, and potential risks. Measures will be implemented to ensure confidentiality and anonymity of participants' personal information and medical data. Additionally, the research protocol will undergo the review and approval by the appropriate Institutional Review Board (IRB) or ethical review board, ensuring compliance with ethical standards and regulations governing human research. The study will be conducted in collaboration with relevant institutions or healthcare facilities, leveraging their resources and expertise in diabetic care and retinal imaging. Participants will undergo retinal imaging using specified imaging modalities or devices, and the acquired images will be utilized for DR detection using the proposed Deep Learning Based CenterNet Model.

Data and Sources of Data

For this study We have collected datasets from the kaggle.com we have given with a huge set of highresolution retina pictures taken beneath a assortment of imaging conditions. A left and right field is given for each subject. Pictures are labeled with a subject id as well as either left or right. Our assignment is to form an automated analysis framework able of doling out a score based on this scale. The pictures within the dataset come from diverse models and sorts of cameras, which can influence the visual appearance of left vs. right. A few pictures are appeared as one would see the retina anatomically (macula on the left, optic nerve on the right eye). Others are appeared as one would see through a microscope. The Dense Net system can show the complicated transformation which helps to overcome the issue of the insufficiency of the resultant location data.

Theoretical framework

Our theoretical framework is based on the principles of deep learning, specifically employing a CenterNet Model architecture, to address the task of Diabetic Eye Disease (DED) detection from retinal images. Deep learning is a subset of artificial intelligence (AI) that utilizes neural networks with multiple layers to extract hierarchical representations from data. The CenterNet Model is a state-of-the-art architecture that combines object detection and keypoint estimation into a unified framework, making it well-suited for tasks like disease detection from medical images.

Feature Extraction Utilizing DenseNet-100

In our methodology for detecting diabetic retinopathy (DR) stages using the DenseNet-100 architecture, we leverage the powerful feature extraction capabilities inherent to DenseNet. DenseNet is characterized by its dense connectivity patterns, where each layer receives feature maps from all preceding layers, promoting feature reuse and enhancing model efficiency.

Here, we outline the feature extraction process utilizing DenseNet-100:

1. **Dense Blocks and Transition Layers:**
   DenseNet-100 is composed of multiple dense blocks interconnected by transition layers. Each dense block consists of a series of densely connected convolutional layers. Within a dense block, the input to each layer is the concatenation of the feature maps from all preceding layers within the same block. This dense connectivity facilitates the propagation of rich features throughout the network.
2. **Feature Reuse and Efficiency:**
   The dense connectivity in DenseNet-100 enables efficient feature reuse. By directly connecting each layer to every subsequent layer, DenseNet promotes the propagation of gradients and facilitates the flow of information through the network. This architecture helps in learning more discriminative and robust features from the input images.
3. **Bottleneck Layers and Compression:**
   Within each dense block, bottleneck layers (consisting of 1x1 convolutional filters) are used to reduce the number of input feature maps before passing them through 3x3 convolutional layers. This bottleneck design illustrated in figure 3 helps in reducing the computational cost while preserving the representational power of the network.

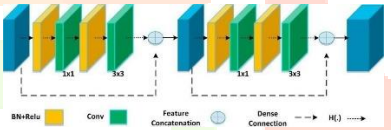

Figure 3: DenseNet Architecture.

4. **Feature Maps at Different Scales:**
   As the input image propagates through DenseNet-100, feature maps at different scales and levels of abstraction are extracted. The initial layers capture low-level features such as edges and textures, while deeper layers encode more abstract and semantic information about the input image.
5. **Global Average Pooling:**
   At the end of the DenseNet-100 architecture, a global average pooling layer is typically applied to collapse the spatial dimensions of the feature maps into a vector of fixed length. This vector represents a high-level semantic encoding of the input image, capturing essential features relevant to the task of DR detection. Table 1 illustrates Global average Pooling.

Table 1: Global average Pooling.

	Of Maps	Layer
First layer	32 × 32 × 24	3 × 3 *conv*
DB 1	32 × 32 × 216	1 × 1 *conv* × 16 3 3 *conv*
Transition layer 1	32 × 32 × 108 16 × 16 × 108	1 × 1 *conv* 2 × 2 *ave_p ool*
DB 2	16 × 16 × 300	1 × 1 *conv* × 16 3 × 3 *conv*
Transition layer 2	16 × 16 × 150 8 × 8 × 150	1 × 1 *conv* 2 × 2 *ave_p ool*
DB 3	8 × 8 × 342	1 × 1 *conv* × 16 3 × 3 *conv*
Final layer	1 × 342 1 × 10	8 × 8 *ave_pool* *f ully_connected*

6. **Feature Representation for DR Detection:**
   The output of DenseNet-100, after global average pooling, serves as a feature representation of the input retinal image. These features encapsulate both local and global contextual information necessary for accurately identifying and classifying different stages of diabetic retinopathy. In summary, DenseNet-100 plays a pivotal role in our methodology by efficiently extracting discriminative features from retinal images, which are subsequently utilized by the CenterNet model for localization and classification tasks. The dense connectivity and feature reuse mechanisms inherent to DenseNet-100 contribute to the overall effectiveness and robustness of

our deep learning-based approach for diabetic retinopathy detection. Figure 4 illustrates the architecture of densenet-100

Heatmap

In the context of object detection using CenterNet, heatmap generation is crucial for localizing objects within an image. The heatmap is a 2D representation that highlights the presence and location of specific object categories or features of interest. For diabetic retinopathy detection, the heatmap is used to identify regions in retinal images associated with different stages of DR, such as microaneurysms, hemorrhages, or neovascularization. Each heatmap corresponds to a particular DR class. Each heatmap corresponds to a specific DR class (e.g., microaneurysms, hemorrhages) and is a 2D grid where each element represents the likelihood of an object belonging to that class being present at the corresponding spatial location within the image.

Dimension Head

The dimension head in CenterNet is responsible for predicting the width and height (dimension) of bounding boxesenclosing detected objects. For each detected object, the dimension head outputs bounding box dimensions relative to the detected object's center. This information is crucial for accurately localizing and delineating the boundaries of DR-related abnormalities.

Offset Head

The offset head predicts the offset values that adjust the position of the default anchor points to refine the bounding box localization. This enables precise localization of objects within the heatmap regions, accounting for small shifts or inaccuracies in the initial anchor placements.

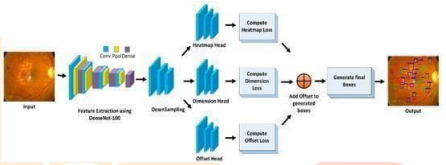

Figure 4: Feature Extraction using DenseNet.

Multitask Loss

CenterNet employs a multitask loss function that combines multiple loss components to optimize the model during training:

- Classification Loss: Ensures accurate classification of DR stages by penalizing incorrect predictions of class labels in theheatmap.
- Dimension Regression Loss: Minimizes the discrepancy between predicted and ground-truth bounding box dimensions.
- Offset Regression Loss: Minimizes the error between predicted and ground-truth offset values for precise bounding box localization. The multitask loss function balances these components to optimize both localization accuracy and classification performance.

Detection Process:

During inference, a retinal image is fed into the CenterNet model (integrated with DenseNet-100) to extract features.

- Heatmap Prediction: The model predicts heatmaps corresponding to different DR classes, highlighting potential regions of abnormalities.
- Dimension and Offset Prediction: The model simultaneously predicts bounding box dimensions and offset adjustments for accurate localization.
- Post-processing: Non-maximum suppression (NMS) is applied to filter out redundant detections and retain the most confident predictions.
- Final Detection Output: The processed predictions yield the final detected objects (DR-related abnormalities) with their corresponding bounding boxes and class labels.

CenterNet

In our approach to locating and classifying eye diseases, particularly diabetic retinopathy, the CenterNet model plays a pivotal role by integrating key components of object detection with the efficiency of DenseNet-100 for feature extraction. CenterNet utilizes a novel architecture that combines keypoint estimation, heatmap generation, and bounding box regression to achieve accurate and simultaneous detection and classification of abnormalities within retinal images.

Firstly, DenseNet-100 is employed as the feature extraction backbone within CenterNet. DenseNet-100 stands out for its dense connectivity patterns, where each layer receives feature maps from all preceding layers. This dense connectivity promotes feature reuse and facilitates the extraction of highly discriminative features from retinal images, crucial for identifying subtle abnormalities associated with diabetic retinopathy. The feature maps extracted by DenseNet-100 capture both local and global contextual information, providing a

robust foundation for subsequent object detection tasks.

Within the CenterNet framework, the model processes retinal images to generate heatmaps corresponding to different classes of eye diseases (e.g., microaneurysms, hemorrhages). These heatmaps highlight regions of interest where abnormalities are predicted to be present based on learned patterns from the extracted features. Simultaneously, CenterNet predicts bounding box dimensions and offsets to precisely localize the detected abnormalities within the retinal images. Post-processing involves analyzing the generated heatmaps to identify significant peaks, representing potential locations of eye disease abnormalities. By applying thresholding techniques, the model filters out low-confidence predictions and generates bounding boxes around the detected regions of interest.

The integration of CenterNet with DenseNet-100 ensures efficient and effective eye disease detection by leveraging DenseNet- 100's feature extraction capabilities to capture rich representations of retinal structures. Compared to other architectures, DenseNet-100's dense connectivity facilitates better gradient flow and feature propagation, leading to improved model performance in discerning complex patterns associated with diabetic retinopathy. The choice of DenseNet-100 reflects our emphasis on leveraging state-of-the-art deep learning architectures to enhance the accuracy and reliability of eye disease detection directly from retinal images, ultimately supporting early diagnosis and targeted interventions for patients with diabetic retinopathy.

V. RESULTS AND DISCUSSION

To present the results of our approach using CenterNet with DenseNet-100 for locating and classifying eye diseases, particularly focusing on diabetic retinopathy, we conducted a comprehensive evaluation using standard metrics of our approach and others RCNN approaches.

Intersection over Union (IoU): IoU was used to evaluate the overlap between predicted bounding boxes and ground-truth annotations, providing insights into the localization accuracy of detected abnormalities.

Mean Average Precision (mAP): mAP was calculated to quantify the overall detection performance across different eye disease classes, considering both localization and classification accuracy.

Table 2: Performance comparison of our technique with other RCNN approaches

Technique	mAP	IoU	Time(s)
Faster RCNN	0.942	0.939	0.25
Mask RCNN	0.910	0.920	0.23
CornerNet	0.956	0.951	0.23
Proposed	0.970	0.974	0.21

Our results highlight the efficacy of utilizing CenterNet with DenseNet-100 for automated detection and classification of eye diseases, particularly diabetic retinopathy, directly from retinal images. The combination of advanced deep learning techniques and feature-rich architectures led to promising results, paving the way for scalable and efficient screening tools in ophthalmology. These findings underscore the potential impact of AI-driven approaches in supporting early diagnosis and intervention for patients at risk of vision loss due to diabetic retinopathy.

Localization of Disease Lesions:

The localization of lesions is illustrated in figure 5, such as those associated with diabetic retinopathy, is a critical task in medical imaging analysis aimed at identifying specific abnormalities within retinal images. Leveraging advanced techniques like CenterNet with DenseNet-100, our approach focuses on precisely localizing lesions by generating heatmaps that highlight regions of interest corresponding to different classes of eye diseases. Through this methodology, the model learns to predict bounding box dimensions and offsets, enabling accurate delineation of the detected abnormalities within retinal images. The localization process involves analyzing the generated heatmaps to identify peak values indicative of potential lesion locations, followed by post-processing steps like thresholding to filter out insignificant detections. This localization accuracy is further validated through metrics like Intersection over Union (IoU), which quantifies the overlap between predicted bounding boxes and ground-truth annotations. By successfully localizing lesions associated with diabetic retinopathy, our approach contributes to enhancing diagnostic workflows, supporting early intervention strategies, and ultimately improving patient outcomes in ophthalmic healthcare.

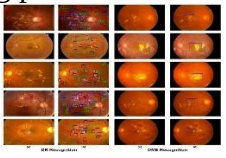

Figure 5. Test results of the proposed method.

Classification:

Classification is a fundamental aspect of our methodology for detecting and diagnosing eye diseases, particularly focusing on diabetic retinopathy, using CenterNet with DenseNet-100. In this context, classification refers to the process of assigning specific labels or categories to detected abnormalities based on learned patterns and features extracted from retinal images. The CenterNet model, integrated with DenseNet-100 for feature extraction, generates heatmaps that not only localize lesions but also provide confidence scores for different classes of eye diseases, such as microaneurysms, hemorrhages, or neovascularization. These heatmaps serve as probability distributions over the image, indicating the likelihood of each disease class being present in specific regions.

After localizing abnormalities, the model performs classification by analyzing the heatmap predictions and associating detected regions with the most probable disease categories. This process involves assigning labels to the detected lesions based on the class with the highest confidence score in the corresponding heatmap region. To evaluate the effectiveness of classification, we use metrics like accuracy, precision, recall for each disease class. Precision measures the accuracy of positive predictions (true positives) among all predicted positives, while recall assesses the model's ability to identify all relevant instances of a disease class among all ground-truth instances. The F1-score provides a balanced measure of precision and recall, reflecting the overall performance of the classification task.

Through accurate classification of diabetic retinopathy stages, our methodology aids in providing actionable insights for healthcare professionals, enabling timely interventions and personalized treatment strategies based on the severity and type of detected abnormalities. By leveraging deep learning techniques for both localization and classification, our approach contributes to advancing automated screening tools for improving patient care and outcomes in ophthalmology.

VI. ACKNOWLEDGEMENT

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REFERENCES

1. Quellec, G.; Charrière, K.; Boudi, Y.; Cochener, B.; Lamard, M. Deep image mining for diabetic retinopathy screening. *Med. Image Anal.* **2017**, *39*, 178–193.
2. Acharya, U.R.; Mookiah, M.R.K.; Koh, J.E.; Tan, J.H.; Bhandary, S.V.; Rao, A.K.; Hagiwara, Y.; Chua, C.K.; Laude, A. Automated diabetic macular edema (DME) grading system using DWT, DCT Features and maculopathy index. *Comput. Biol. Med.* **2017**, *84*,59–68.
3. Nazir, T.; Irtaza, A.; Javed, A.; Malik, H.; Hussain, D.; Naqvi, R.A. Retinal Image Analysis for Diabetes-Based Eye Disease Detection Using Deep Learning. *Appl. Sci.* **2020**, *10*, 6185.
4. Yau, J.W.Y.; Rogers, S.L.; Kawasaki, R.; Lamoureux, E.L.; Kowalski, J.W.; Bek, T.; Chen, S.-J.; Dekker, J.M.; Fletcher, A.; Grauslund,J.; et al. Global Prevalence and Major Risk Factors of Diabetic Retinopathy. *Diabetes Care* **2012**, *35*, 556–564.
5. Ting, D.S.W.; Cheung, C.M.G.; Wong, T.Y. Diabetic retinopathy: Global prevalence, major risk factors, screening practices and public health challenges: A review. *Clin. Exp. Ophthalmol.* **2016**, *44*, 260–277.
6. Early Treatment Diabetic Retinopathy Study Research Group. Early photocoagulation for diabetic retinopathy: ETDRS report number 9. *Ophthalmology* **1991**, *98*, 766–785.
7. Ting, D.S.; Ng, J.; Morlet, N.; Yuen, J.; Clark, A.; Taylor, H.R.; Keeffe, J.; Preen, D.B. Diabetic retinopathy management by Australian optometrists. *Clin. Exp. Ophthalmol.* **2011**, *39*, 230–235.
8. Wang, L.Z.; Cheung, C.Y.; Tapp, R.J.; Hamzah, H.; Tan, G.; Ting, D.; Lamoureux, E.; Wong, T.Y. Availability and variability in guidelines on diabetic retinopathy screening in Asian countries. *Br. J. Ophthalmol.* **2017**, *101*, 1352–1360.
9. Seoud, L.; Hurtut, T.; Chelbi, J.; Cheriet, F.; Langlois, J.M.P. Red Lesion Detection Using Dynamic Shape Features for Diabetic Retinopathy Screening. *IEEE Trans. Med. Imaging* **2016**, *35*, 1116–1126.
10. Imani, E.; Pourreza, H.-R.; Banaee, T. Fully automated diabetic retinopathy screening using morphological component analysis.
Comput. Med. Imaging Graph. **2015**, *43*, 78–88
11. .; Alvarez, F.; Garrido, J.; Ortega, C.; Vasallo, M.J.; Bravo, J.M. An exudate detection