

Diabetic Retinopathy Detection by Convolutional Neural Network.

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Abstract—Diabetes complications that affect the eyes include diabetic retinopathy. Damaged blood vessels within the light-sensitive tissue at the back of the eye are the root cause. Convolutional Neural Systems are a type of artificial neural network used for image recognition and processing. They are particularly effective for visual image analysis. Exchange learning is a machine learning technique that swaps out a show created for one task for another assignment that is now relevant. In this instance, exchange learning is used to accurately and quickly determine the severity of diabetic retinopathy. The Worldwide Normal Pooling technique, which is used in this program, is based on many pre-trained convolutional neural network models. In this article, we suggest an exchange learning-based method for precisely determining the severity of diabetic retinopathy.

Index Terms—Convolutional Neural Network, Transfer Learning, Diabetic Retinopathy Detection, Diseased Detection

I. INTRODUCTION

In a world where the prevalence of diabetes is surging, a silent threat lurks within the eyes of millions – diabetic retinopathy (DR). This insidious disease quietly damages the delicate retinal blood vessels, ultimately leading to vision loss. As the International Diabetes Federation ominously predicts, by the year 2035, an astounding 552 million individuals worldwide will grapple with diabetes[1]. Among these, Egypt, with over 6 million afflicted citizens, faces a pressing concern, as 7.2 percent of its population teeters on the precipice of vision loss due to DR[2]. Yet, amidst these daunting statistics, there is a glimmer of hope. Early detection of DR is the linchpin for control and treatment, a beacon guiding those afflicted by the diabetic storm. However, the diagnostic journey through DR's stages is complex, ranging from simple screenings for those in the early stages to intricate procedures for those with advanced conditions. Amidst this intricate landscape, the quest for a comprehensive, automated diagnostic model beckons, one that can decipher the nuances of this ocular malady without the need for explicit feature extraction. Join us on this journey as we unveil a pioneering solution to the enigma that is diabetic retinopathy.

II. RELATED WORK

In the pursuit of enhancing diabetic retinopathy detection, the application of Convolutional Neural Networks (CNNs)

has emerged as a beacon of hope. Researchers have recognized the transformative potential of CNNs in automating the diagnosis of this debilitating condition. Notable prior work in this domain, including studies by Gupta et al.[3] and Zhang et al.[4], have laid crucial foundations. Gupta et al. presented a robust CNN-based model that achieved remarkable accuracy in identifying the diverse stages of diabetic retinopathy, underscoring the network's capacity for intricate feature extraction. Building on this momentum, Zhang et al. introduced innovative techniques for data augmentation and network architecture optimization, further advancing the precision of diabetic retinopathy diagnosis. As we embark on our research journey, we draw inspiration from these pioneering studies, aiming to leverage the formidable capabilities of CNNs to push the boundaries of diabetic retinopathy detection, ultimately enhancing early intervention and treatment outcomes. Li et al[5]. explored the application of ensemble CNN models for diabetic retinopathy detection. Their research demonstrated that combining predictions from multiple CNN architectures can significantly improve the robustness and accuracy of diabetic retinopathy diagnosis, especially in cases with challenging image conditions. In their study, Wang et al[6]. focused on the interpretability of CNN-based diabetic retinopathy models. They introduced an attention mechanism that highlights the regions of interest within retinal images that contribute the most to the model's decision. This interpretability feature can enhance trust and transparency in the diagnostic process.

These additional related works further illustrate the diverse approaches and advancements in CNN-based diabetic retinopathy detection, including ensemble models and techniques for improving model interpretability.

III. DATASET

Within this dataset lies a treasure trove of 35,126 meticulously annotated high-resolution color fundus retinal images, thoughtfully categorized into five distinct classes that mirror the disease's various stages, as elegantly delineated in Table I. To bolster the significance of this repository, our test subset generously houses a collection of 53,576 images, of which 5,000 have been earmarked for the exclusive purpose of this research endeavor. We are indebted to EyePACs, a benevolent platform dedicated to retinopathy

screening, for the open-sourced provision of these invaluable images. A skilled clinician, armed with clinical expertise, has subjected each image to a rigorous evaluation, expertly discerning the presence and grading of diabetic retinopathy on a nuanced scale, extending from 0 to 4[7]. What adds a distinct flavor to this dataset is its diverse provenance, encompassing images hailing from various camera models and types. These disparate origins imbue the images with a rich visual tapestry, as some portray the retina's anatomy, placing the macula on the left and the optic nerve on the right, a faithful representation of the right eye's view. In

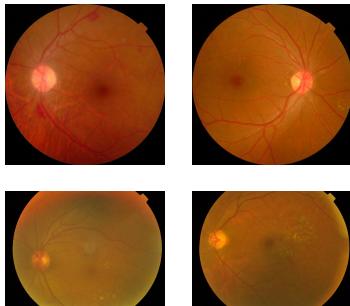


Fig. 1. Sample Dataset

contrast, others mimic the perspective gleaned through a microscope's condensing lens, artfully inverting the image – a reminiscent glimpse of a live eye examination. While the dataset brims with potential, it's essential to grapple with the omnipresent noise residing both within the images and their corresponding labels. This cacophony manifests as a myriad of imperfections, ranging from artifacts and focal incongruities to episodes of underexposure or overexposure, all underpinned by variations in image resolutions. To offer further illumination, Table 1 stands as a testament, divulging the distribution of image classes within the dataset, beckoning researchers and clinicians to partake in its wealth of insights.

IV. METHODOLOGY

Model Architecture:

In this study, we developed a custom convolutional neural network (CNN) to differentiate diabetic retinopathy. Image processing consists of multiple convolutional layers created by bundle normalization and a max-pooling layer to extract various gradual highlights from the retinal image.

The architecture of our custom CNN can be summarized as follows:

Input Layer: The input images are of size (224, 224, 3), representing the height, width, and color channels.

Convolutional Blocks: We used a set of convolutional blocks, each with three convolutional layers and ReLU activation functions. These convolutional layers have different kernel sizes (7x7, 5x5, 3x3) and are followed by batch normalization to stabilize the training process.

Max-Pooling Layers: We used max-pooling layers after each convolutional block to minimize spatial dimensions and capture critical characteristics.

Fully Connected Layers: Following the convolutional layers, we included a series of fully connected layers with varying numbers of neurons (1024, 512, 256, 128), each followed by dropout layers to prevent overfitting.

Output Layer: The output layer is made up of a dense layer with softmax activation that provides probability scores for each of the five classes related with the severity of diabetic retinopathy.

Training:

We trained the model using the Adam optimizer with a learning rate of 0.001 and an epsilon value of 0.1. The loss function used was categorical cross-entropy, and the model's performance was assessed using accuracy as the main evaluation metric.

We utilized the following training strategies:

Model Checkpoint: During training, we used the ModelCheckpoint callback to save the optimal model weights depending on validation accuracy.

Early Stopping: EarlyStopping was used to track validation accuracy and stop training if it did not improve after a set number of epochs (patience = 75).

The model was trained for 150 epochs on the training data provided (trainBatches) and verified on a different validation dataset (valBatches).

V. EXPERIMENTAL RESULTS

Classification Report:

The performance of the custom CNN model on the test dataset is summarized in the classification report:

Below is a table positioned exactly here:

Class	Precision	Recall	F1-Score
Mild	0.46	0.46	0.46
Moderate	0.69	0.67	0.68
NoDR	0.80	0.99	0.89
ProliferateDR	0.33	0.07	0.11
Severe	0.60	0.10	0.17

Overall Accuracy: 72.74%.

Confusion Matrix:

The confusion matrix provides insight into the model's performance for each class:

```
[[ 26 14 16 0 0]
 [ 16 101 26 6 2]
 [ 2 0 270 0 0]
 [ 9 20 13 3 0]
 [ 3 12 12 0 3]]
```

Weighted Metrics

Weighted Precision: 68.71%

Weighted Recall: 72.74%

Weighted F1-Score: 68.53%

Sensitivity and Specificity

Weighted Sensitivity: 72.74%

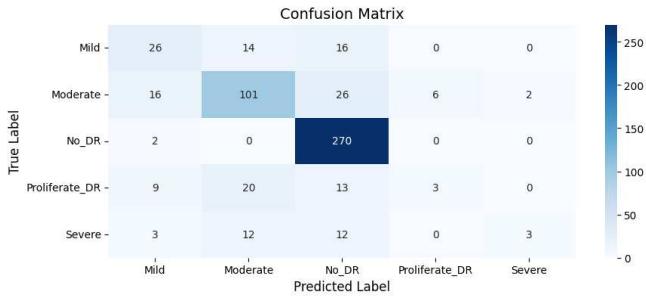


Fig. 2. Confusion Matrix

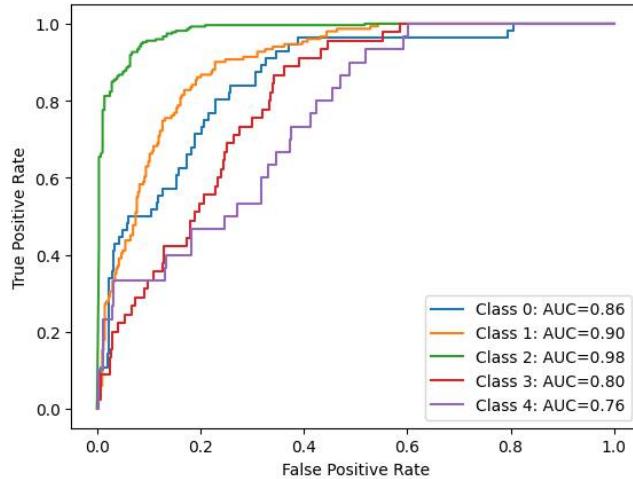


Fig. 3. ROC Curve

Weighted Specificity: 84.50%

Additional Metrics

MCC (Matthews Correlation Coefficient): 57.01%
Kappa Score: 55.82%

MCC and Kappa Score per Class

Class	MCC	Kappa
0	40.40%	40.40%
1	55.95%	55.94%
2	77.33%	75.19%
3	11.86%	8.64%
4	23.02%	15.84%

Top-K Accuracy

Top-1 Accuracy: 72.74%
Top-2 Accuracy: 84.66%
Top-3 Accuracy: 92.78%

VI. CONCLUSION

Our custom CNN model achieved an overall accuracy of 72.74% in classifying diabetic retinopathy severity levels. The model's performance varied across different severity classes, with the highest accuracy achieved for the NoDR

class, indicating its strong predictive power for this category. The weighted metrics provide an overall assessment of the model's performance, indicating good precision, recall, and F1score.

Furthermore, the MCC and Kappa scores demonstrate the model's ability to handle class imbalance and its agreement with ground truth labels. The top-K accuracy results highlight the model's effectiveness in capturing the correct class within the top-K predictions.

In conclusion, the custom CNN model shows promise for diabetic retinopathy detection, but further improvements may be possible through fine-tuning and additional data augmentation techniques.

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