Using Retina Pictures to Detect Diabetic Eye Disease

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Abstract. Diabetic Retinopathy (DR) is a significant cause of global vision loss. Caused by high blood sugar damaging the retina, the condition can be slowed down with early diagnosis and intervention. This report covers the development of a system to classify different stages of DR through retina imaging. Using a combination of a ResNet18 network along with MASK RCNN for Lesion Detection and Segmentation, our sequential system managed to identify five different stages of diabetic retinopathy with an accuracy of 79.81

Keywords: Diabetic Retinopathy · Vision Loss · Vision Impairment · Diabetes · Machine Learning · DR Screening.

1 Introduction

Diabetic Retinopathy (DR) stands as a critical concern in the realm of healthcare, particularly due to its significant impact on vision loss within the global population. With projections indicating that by 2040, around 600 million individuals will grapple with diabetes—a leading precursor to DR—the urgency for effective screening methods becomes paramount. Early intervention in DR has been proven instrumental in slowing down its progression, thereby averting potential vision impairment.[1] Despite the pressing need for timely detection, the current diagnostic process remains arduous and manual, relying heavily on the expertise of trained clinicians for evaluation.[2]

In light of these challenges, there arises a compelling motivation to develop an automated analysis system capable of swiftly and accurately identifying the presence of DR in retinal images. This report delves into the development of such a system, which aims not only to assign scores indicative of DR severity but also to account for noise, anomalies, and the potential inversion of images. By leveraging advancements in technology and machine learning, the ultimate goal is to revolutionize DR screening, facilitating early detection and intervention to mitigate its debilitating effects.

The rest of the report is divided as follows. In section 2 the report covers the materials used throughout the project, section 3 discusses our methods, and section 4 discusses our results. Sections 5 and 6 cover our accomplishments and contributions, and finally, section 7 concludes our report while section 8 addresses future work.

1.1 Related Works

In 2021, a collaborative effort from individuals in Shanghai resulted in the creation of DeepDR, a deep-learning system designed to identify diabetic retinopathy. Utilizing authentic DR screening datasets, this system attained remarkable sensitivity and accuracy in detecting DR across all stages, from its early manifestations to its advanced forms. [1] Meanwhile, in the United States, Anika, an eighth-grader from California, earned recognition as one of the 30 finalists in the esteemed Broadcom Masters Competition for her project. She developed a method for diagnosing diabetic diseases using convolutional neural networks. Her model, trained on a dataset comprising 24,500 images of the human retina, showcased the synergy between human effort in organizing and preparing data and the advancements in AI technology, highlighting how collaboration can enhance outcomes.[3] And of course, since we are completing a Kaggle challenge, several others have completed this project, 661 teams to be specific. [2]

2 Materials

The application is developed, trained, and tested with a data collection of high-resolution retina images.

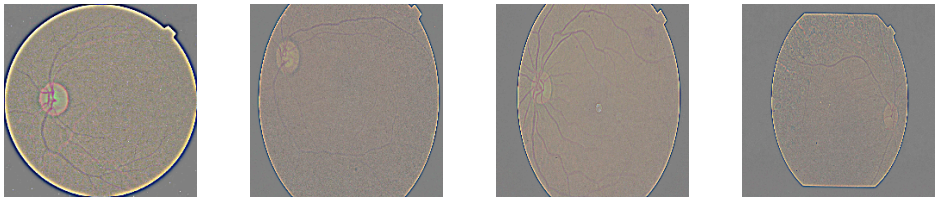
2.1 Data

Testing data is a dataset that contains retina images pre-categorized by a clinician in severity of diabetic retinopathy, as shown in Figure 1. Classification is based on a zero to four-point scale:

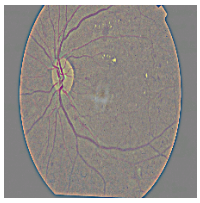
0. None
1. Mild
2. Moderate
3. Severe
4. Proliferative

We use an additional dataset for lesion detection and segmentation. It consisted of retina images and ground truth images for lesions, shown in Figure 2:

0. Microaneurysms
1. Haemorrhages
2. Hard Exudates
3. Soft Exudates

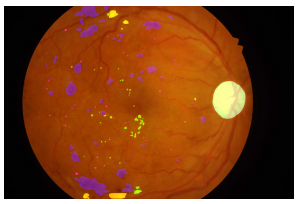


(a) None (b) Mild (c) Moderate (d) Severe

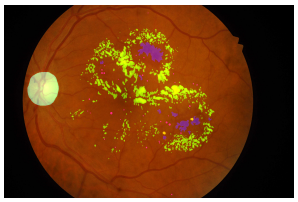


(e) Proliferative

Fig. 1: Examples of the 5 different classifications of diabetic retinopathy



(a) IDRid 55



(b) IDRid 75

Fig. 2: Retinal lesions. Microaneurysms: Magenta, Haemorrhages: Blue, Hard Exudates: Green, Soft Exudates: Cyan, Optic Disk: Yellow

3 Methods

To tackle this project, we devised the DeepDR system comprising two sub-networks: one for DR grading and another for lesion-aware analysis, both built upon ResNet, a residual network architecture, with the lesion-aware component leveraging Mask-RCNN, a convolutional neural network architecture, as well. In our approach, ResNet and Mask-RCNN served as feature extractors, processing input images to generate relevant features.

Development of the system was divided into five stages as shown in Figure 3:

1. Preprocessing
2. ResNet18
3. Lesion Detection Module
4. Lesion Segmentation Module
5. DR Grading Sub-network

Fig. 3: Stages of development.

3.1 Preprocessing

From the pool of 3662 images sourced from Kaggle[2] for DR grading, we applied normalization to the image to scale the pixel values from 0-1, using channel-specific means and standard deviations for standardization. This process aids in standardizing the input data, a crucial step that can enhance model convergence during training. The dataset had previously been processed with Gaussian filtering to enhance image quality by reducing noise. Despite these enhancements, we encountered a significant challenge: class imbalance. To address this, we employed a weighted sampling strategy during the training phase. By assigning higher sampling probabilities to underrepresented classes, we aimed to achieve a balanced exposure of the model to all classes, thereby improving its diagnostic accuracy across the spectrum of diabetic retinopathy severity. This ensures that the model sees a more balanced distribution of classes during training, thereby improving its ability to generalize to all classes equally. Thereby mitigating the effects of class imbalance.

For the lesion-aware subnetwork, approximately 80 images were sourced from the Indian Diabetic Retinopathy Image Dataset[4], and likewise partitioned for training and validation akin to the DR grading task. In this case, instead of employing flips and rotations, the images were directly resized to 224 by 224 pixels, followed by conversion to tensor format and subsequent normalization.

3.2 ResNet18

We utilized a ResNet18-based deep learning network trained on an extensive ImageNet dataset. This initial training enables the network to extract generalized features from diverse images across various categories. By fine-tuning this model on our DR-specific dataset, we refine its capability to detect and classify features relevant to diabetic retinopathy and its various stages.

To illustrate this process, consider our network's layers as floors in a building, The initial layers have been trained on ImageNet data. At the very top, the final layer is our customized dataset.

For our purpose, ResNet18 serves a dual role: as a foundation for lesion detection and as a backbone for our lesion segmentation module.

3.3 Lesion Detection Module

The lesion detection model is customized from the ResNet18 architecture by replacing the final fully connected layer to accommodate the classification of four distinct lesion types. This module uses the information and weights learned from the previous RestNet18 basis to help facilitate lesion detection, while acting as a multi-label classifier to evaluate the data. This evaluation classifies it into one of four lesion types mentioned previously.

3.4 Lesion Segmentation Module

The lesion segmentation module utilizes a Mask-RCNN architecture, a variant of R-CNN that adds a branch for predicting segmentation masks on each Region of Interest (RoI), modified to operate on the feature maps produced by our lesion detection model. This decisions reuses the application of learned features towards the segmentation of lesions instead, which in turn facilitates a more detailed analysis and interpretation of lesion characteristics.

The segmentation process is powered by a custom sub-network from the ResNet18 model, equipped with a Feature Pyramid Network (FPN). This configuration enables the model to capture a comprehensive range of features across different scales, which is crucial for accurately identify lesion boundaries. Preloaded with fine-tuned weights, it serves as a robust feature extractor, and is further refined through the segmentation task.

3.5 DR Grading Sub-network

Our DR grading network brings together the features extracted from both the ResNet18 sub-network along our lesion detection and segmentation modules. This combination allows our model to leverage both the general features, as well as the specific lesion characteristics identified by the lesion segmentation module.

The combined features are then fed into a fully connected layer, which has been thus far trained to interpret these features in the context of diabetic retinopathy severity. The output of this layer is then passed through a softmax

function to yield a probability distribution over the possible DR grades. This probability output facilitates the interpretation of grading results, providing not just a single grade but rather a more nuanced view of the model's confidence across the whole grading spectrum.

4 Results

We executed each module in sequential order, and since the results of each one affected subsequent modules, this order was very important. We opted to run each module over 35 epochs to ensure robust evaluation during testing, and after completing system training and testing, we generated accuracy and loss scores for each step, alongside the system's final performance metrics to evaluate our results.

Table 1 presents the results obtained at different stages of our framework:

Table 1: Results for different steps

(a) Training Data

Step	**Accuracy (%)**	**Loss**
ResNet18	99%	0.0007
Detection	-	0.003
Segmentation	-	1.82
DR Grading	-	1.09

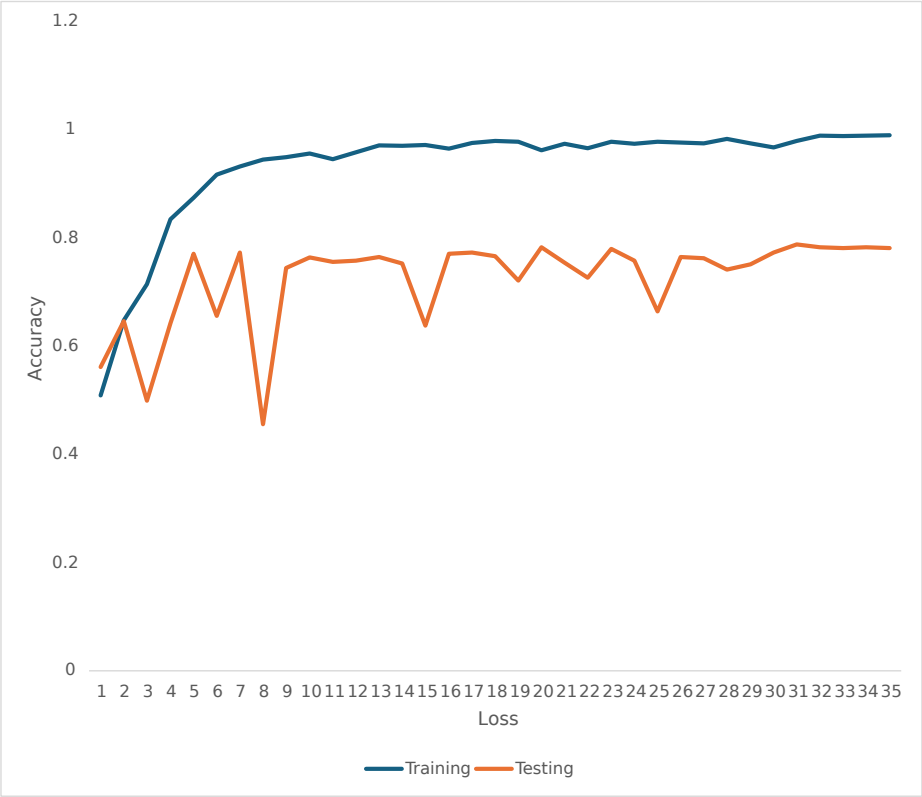
(b) Testing Data

Step	**Accuracy (%)**	**Loss**
ResNet18	78.17%	0.038
DR Grading	79.81%	1.33

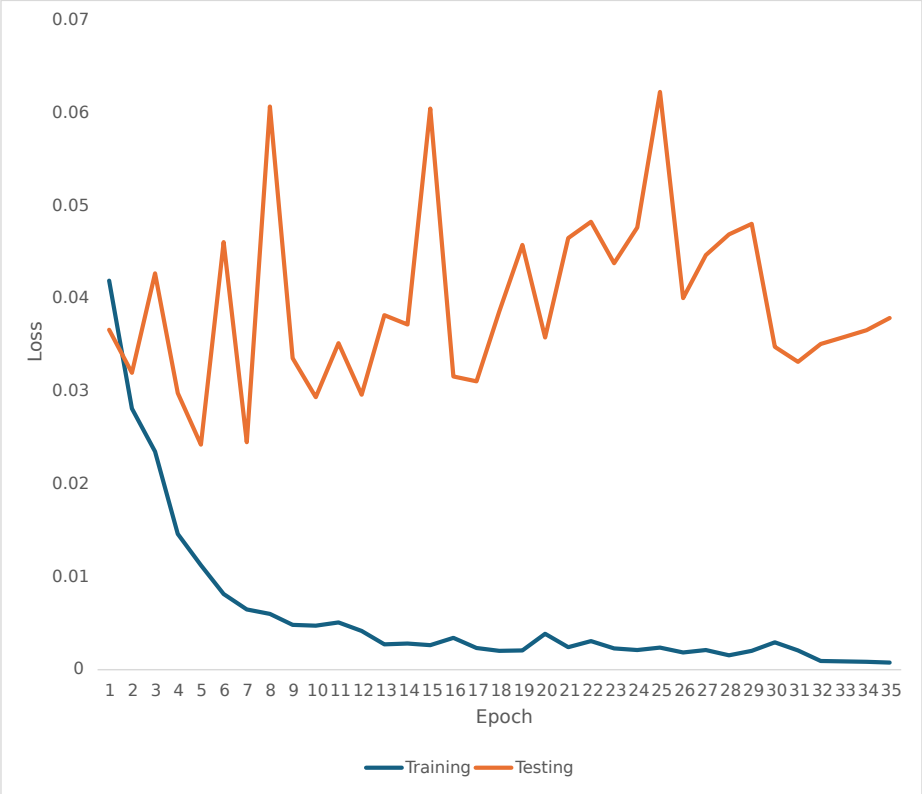
Our analysis consistently demonstrates high accuracy across all modules, culminating an overall accuracy of 79.81% for the entire system.

4.1 ResNet18

In the ResNet18 stage, we achieved a testing accuracy of around 72.57%, with a minimal loss of approximately 0.039. These results, also shown in Figure 4 showcase the robust nature of the ResNet18 foundation, achieving a high-accuracy and low-loss result. Having a strong foundation for our system is beneficial as it also provides additional training information for sequential steps.



(a) Accuracy over Time



(b) Loss over Time

Fig. 4: ResNet18 Accuracy and Loss over Time (Epochs)

4.2 Detection and Segmentation

Using the training from ResNet18 as a basis, we train the lesion detection and segmentation modules in order, respetcively. This process did not yield high accuracy scores but provides us with a final loss of 0.038 for segmentation, and 1.33 for detection. Observing Figure 5 and 6, we can see that both modules see a significant decrease in loss for each subsequent epoch.

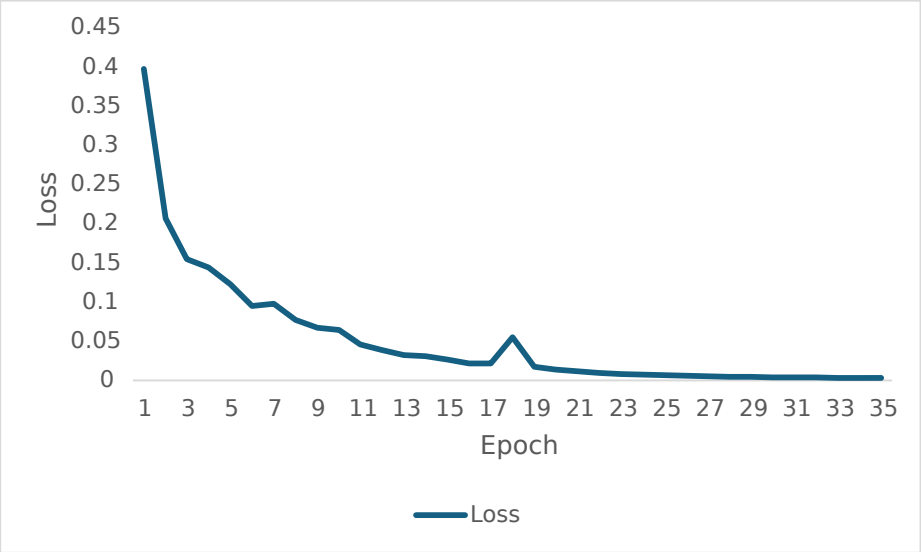


Fig. 5: Lesion Detection Loss over Time (Epochs)

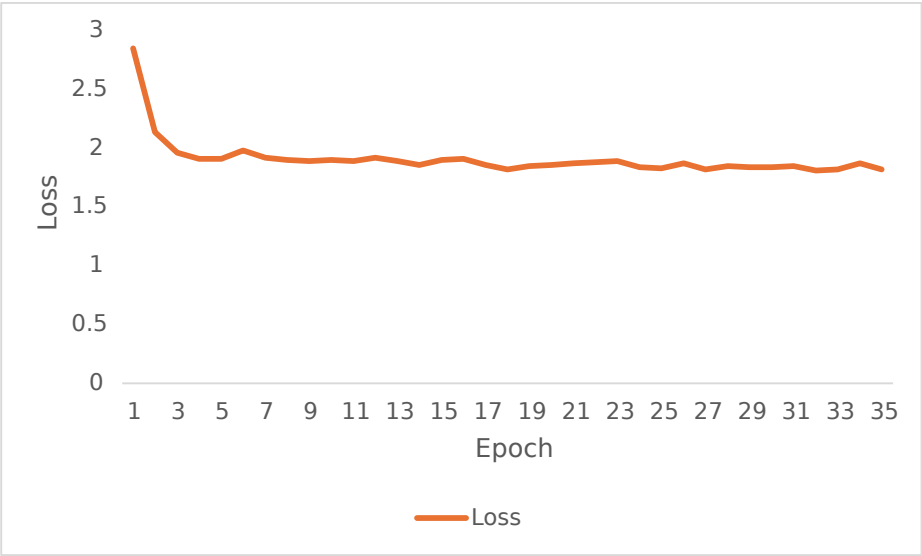


Fig. 6: Lesion Segmentation Loss over Time (Epochs)

4.3 DR Grading

In the final stage of our methodology, the DR Grading SubNetwork, which integrates the foundational ResNet18 with the lesion detection and segmentation modules, was tested extensively. This phase culminated in a testing accuracy of 79.81%. Figure 7 indicates the performance level of our model in the context of diabetic retinopathy grading. The testing accuracy we achieved provides insight into the model's ability to utilize learned features from both the ResNet18 architecture and the specialized lesion analysis modules effectively. a

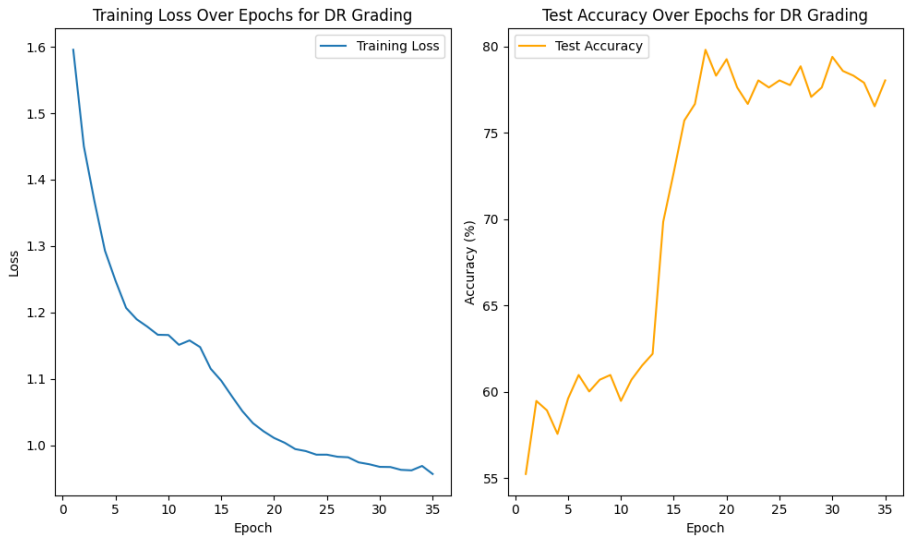


Fig. 7: DR Grading Accuracy and Loss over Time (Epochs)

5 Accomplishments

Through conception, creation, and testing, we managed to create a system capable of detection and classification of various stages of Diabetic Retinopathy.

Our system manages to use multiple methods to train and improve recognition of DR. By using ResNet18 as a basis, we implemented a system with both robust and precise learning. This milestone in testing accuracy highlights the model's capability to accurately classify the stages of diabetic retinopathy, leveraging the deep feature representations learned from both the ResNet18 backbone and the lesion-specific insights gained from the detection and segmentation phases. It reaffirms our hypothesis that a layered, methodical approach to DR analysis—starting from a strong foundational model, through targeted lesion detection, to detailed segmentation—culminates in a highly effective grading system.

6 Contributions

The project idea was brought to discussion by Bhakti, which our group voted on proceeding with. Development of the project, report, and demo video was split within the group:

- **Chirajay Aggarwal**: Developed Lesion Segmentation and Detection; documented system in README file.
- **Bhakti Bhanushali**: Implemented BaseDR Model (ResNet18); developed Lesion Segmentation and Detection; created final DR Grading module.
- **Matthew Lee**: Documented and summarized Materials, Methods, and Results sections of the report; further expanded on Conclusion and Discussions, Future work, and Abstract; formatted and refined report.
- **Ketan Dhingra**: Created final DR Grading module; documented system in README file.
- **Jessica Li**: Documented and summarized Introduction, Related Works, and Methods (Intro and Preprocessing) sections of the report; formatted the report document and made heavy refinements throughout; outlined and created project demo video and slide deck.

7 Conclusion and Discussions

This project aimed to develop an automated system for the detection and grading of diabetic retinopathy in retinal images. By leveraging different methods in computer vision and machine learning, our system achieved very promising results in terms of accuracy and loss across each module built. Using ResNet18 as a basis for our module shows a great increase in accuracy and a decrease in loss for each further epoch. Future iterations of this project can improve on dataset usage, fine-tuning each module, and potentially incorporating additional relevant data to train on.

8 Future Work

While the current model can correctly identify DR to an accurate degree, future development on this system could implement several strategies to produce better accuracy and use.

8.1 Training on Additional Data

Although the system already contains a substantial dataset comprising diverse examples of DR, appending additional data to train ono and with a broader spectrum imaging could further enhance the model's accuracy.

8.2 Fine-tuning Training Parameters

Further inquiry into more effective parameters for each module could help refine the system further. This exploration could potentially enable the system to better comprehend and analyze the data, yielding higher accuracy and/or lower loss results.

8.3 Integration of Personalized Information

The existing system solely relies on retina imaging for predicting and classifying the presence of DR. Expanding the system to incorporate additional relevant information, such as medical history and patient symptoms, could potentially enhance the system's diagnostic capabilities for Diabetic Retinopathy.

However, this expansion involves integrating more personalized medical information, which can complicate matters concerning patient privacy. Ensuring the privacy and protection of an individual's medical information may necessitate obtaining explicit consent and could potentially prolong the process. This may not align with the system's need for a substantial volume of data.

Acknowledgments

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