



Detecting Diabetic Retinopathy using Deep Learning

November 18, 2019



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

Presented By:

Subhajit Barh

Department of Mathematics

(Computer Science and Data Processing)

Indian Institute of Technology Kharagpur





*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

1 *Introduction*

2 *Convolutional Neural Network*

3 *Transfer Learning*

4 *Data*

5 *Training and Finetuning*

6 *Result*

7 *Deficiency*

8 *Improvement*

9 *References*



What is Diabetic Retinopathy?

4

Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

What is DR

Detecting DR

Detecting DR using Deep
Learning

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

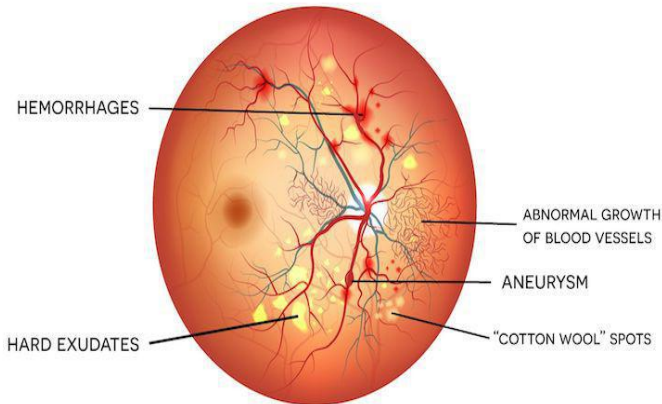
Result

Deficiency

Improvement

References

Diabetic retinopathy (DR), also known as diabetic eye disease, is a medical condition in which damage occurs to the retina due to diabetes mellitus. It is a leading cause of blindness. Diabetic retinopathy affects up to 80 percent of those who have had diabetes aged 20 years or more.





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

What is DR

Detecting DR

Detecting DR using Deep
Learning

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References

Depending on severity we can divide Diabetic Retinopathy in 5 categories

0 - No DR

1 - Mild

2 - Moderate

3 - Severe

4 - Proliferative DR



Manual Detection

Detecting Diabetic Retinopathy is currently done by a method called Dilated eye exam . In this method the doctor administers drops in patient's eye and take pictures of the retina. After reviewing the image doctor have to manually conclude about the presence or advance of the disease . The doctor or experts generally looks for abnormalities in the blood vessels, optic nerve, retina, or formation of new blood vessels, retinal detachment, scar tissue etc .



Manual Detection

Detecting Diabetic Retinopathy is currently done by a method called Dilated eye exam . In this method the doctor administers drops in patient's eye and take pictures of the retina. After reviewing the image doctor have to manually conclude about the presence or advance of the disease . The doctor or experts generally looks for abnormalities in the blood vessels, optic nerve, retina, or formation of new blood vessels, retinal detachment, scar tissue etc .

Automated Detection

An automated tool for grading severity of diabetic retinopathy would be very useful for accelerating detection and treatment. We will use a Deep learning convolutional neural network model to detect Diabetic Retinopathy with minimum human intervention .



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

What is DR

Detecting DR

*Detecting DR using Deep
Learning*

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

We will use Convolutional Neural Network along with transfer Learning to detect and categorize the presence of diabetic Retinopathy



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

What is CNN

Back Propagation

Gradient Descent

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References

CNN

CNN(convolutional Neural Network) is an neural network architecture which works really well with Images. Each Convolution Layer Consists of mainly three sub layers.

- 1 Convolution layer
- 2 Pooling Layer
- 3 Fully Connected Layer



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1 _{x1}	1 _{x0}	0 _{x1}	0
0	1 _{x0}	1 _{x1}	1 _{x0}	0
0	0 _{x1}	1 _{x0}	1 _{x1}	1
0	0	1	1	0
0	1	1	0	0

Image

4	3	

Convolved
Feature



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1 _{x1}	0 _{x0}	0 _{x1}
0	1	1 _{x0}	1 _{x1}	0 _{x0}
0	0	1 _{x1}	1 _{x0}	1 _{x1}
0	0	1	1	0
0	1	1	0	0

Image

4	3	4

Convolved
Feature



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1	0	0
0 _{x1}	1 _{x0}	1 _{x1}	1	0
0 _{x0}	0 _{x1}	1 _{x0}	1	1
0 _{x1}	0 _{x0}	1 _{x1}	1	0
0	1	1	0	0

Image

4	3	4
2		

Convolved
Feature



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1	0	0
0	1 _{x1}	1 _{x0}	1 _{x1}	0
0	0 _{x0}	1 _{x1}	1 _{x0}	1
0	0 _{x1}	1 _{x0}	1 _{x1}	0
0	1	1	0	0

Image

4	3	4
2	4	

Convolved
Feature



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1	0	0
0	1	1 _{x1}	1 _{x0}	0 _{x1}
0	0	1 _{x0}	1 _{x1}	1 _{x0}
0	0	1 _{x1}	1 _{x0}	0 _{x1}
0	1	1	0	0

Image

4	3	4
2	4	3

Convolved
Feature



In convolution layer the filter(a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1	0	0
0	1	1	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0 _{x0}	0 _{x1}	1 _{x0}	1	0
0 _{x1}	1 _{x0}	1 _{x1}	0	0

Image

4	3	4
2	4	3
2		

Convolved
Feature



In convolution layer the filter(a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1	0	0
0	1	1	1	0
0	0 _{x1}	1 _{x0}	1 _{x1}	1
0	0 _{x0}	1 _{x1}	1 _{x0}	0
0	1 _{x1}	1 _{x0}	0 _{x1}	0

Image

4	3	4
2	4	3
2	3	

Convolved
Feature



In convolution layer the filter (a smaller dimensional matrix) moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed. In each step it computes the dot product with the original matrix and thus constructs the output matrix.

1	1	1	0	0
0	1	1	1	0
0	0	1 _{x1}	1 _{x0}	1 _{x1}
0	0	1 _{x0}	1 _{x1}	0 _{x0}
0	1	1 _{x1}	0 _{x0}	0 _{x1}

Image

4	3	4
2	4	3
2	3	4

Convolved
Feature



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature

There are two types of Pooling: Max Pooling and Average Pooling.

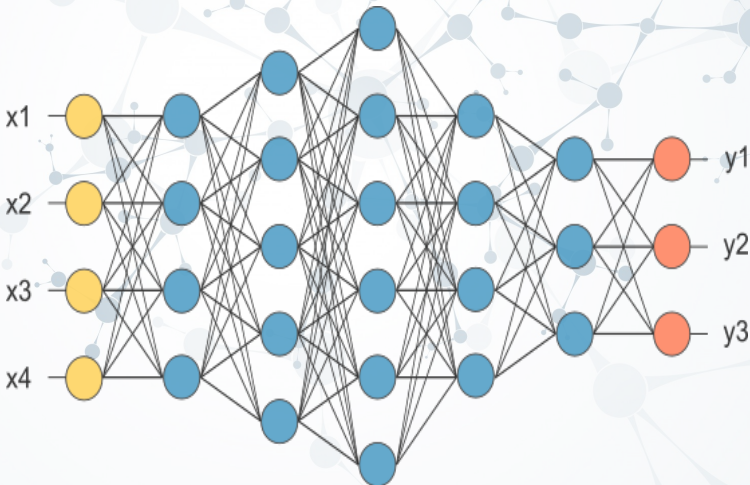
Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1



The fully connected layer is nothing but a ordinary perception based network. Here we flattened our matrix into vector and feed it into a fully connected layer like any other neural network.





*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

What is CNN

Back Propagation

Gradient Descent

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

All those filters have weights. Those weights and perceptron weights in FC layers must be learned using back-propagation . In each iteration we update those weights using our optimizer. Here we used Gradient Descent optimizer. But in future we can use optimizers like adam or adaguard etc.



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

What is CNN

Back Propagation

Gradient Descent

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References

Gradient Descent

Gradient descent is an iterative optimization algorithm for finding the minimum of a function. To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient (or approximate gradient) of the function at the current point



Cost function or error function can be an indicator of how accurate our model is and optimizer uses that to optimize our model. Here we will use MSE loss. Which is defined as

$$J(w, b) = \frac{1}{M} \sum (h_{(w,b)}(x^{(i)}) - y^{(i)})^2 \quad (1)$$

Then we calculate gradients of the cost function as below

$$\nabla_w J = \frac{\partial}{\partial w} J(w, b) \quad (2)$$

$$\nabla_b J = \frac{\partial}{\partial b} J(w, b) \quad (3)$$

Then we update the weights using the formula as below

$$w' = w - \alpha \nabla_w J \quad (4)$$

$$b' = b - \alpha \nabla_b J \quad (5)$$



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

What is CNN

Back Propagation

Gradient Descent

Transfer
Learning

Data

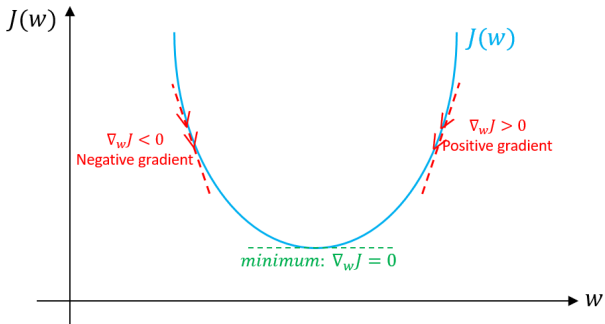
Training and
Finetuning

Result

Deficiency

Improvement

References





*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

*What is Transfer Learning
Pretrained Models*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

Transfer learning is a process in which we make use of the knowledge gained while solving one problem and applying it to a different but related problem .



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

What is Transfer Learning

Pretrained Models

Data

Training and
Finetuning

Result

Deficiency

Improvement

References

Here we use a pre-trained big model named resnext101(44 million parameters) which was trained by facebook on Imagenet . We take the resnext101 model chop the last layer down and add our custom regression layer to classify the images.



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

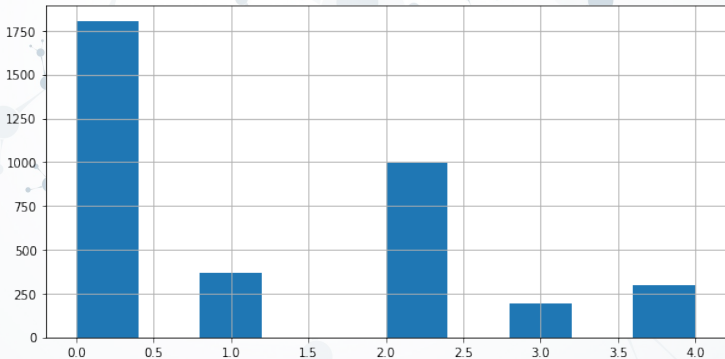
Result

Deficiency

Improvement

References

Asia Pacific Tele-Ophthalmology Society (APTOS) and Aravind Eye Hospital of India published a dataset of retina images through Kaggle. The Data-set can be found on <https://www.kaggle.com/c/aptos2019-blindness-detection/data> With quick exploration we can visualize the data as follows





Detecting Diabetic Retinopathy using Deep Learning

Introduction

Convolutional Neural Network

Transfer Learning

Data

Training and Finetuning

Training
FineTuning

Result

Deficiency

Improvement

References

First we train the model freezing the base layers. we do this for 30 epochs we used

- 1 Gradient Descent as Optimizer
- 2 learning rate=0.001
- 3 cost function is Mean Square Error



Detecting Diabetic Retinopathy using Deep Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Training
Finetuning

Result

Deficiency

Improvement

References

Then we fine Tune the whole model for another 30 epochs .Here we unfreeze the base layer

- 1 Gradient Descent as Optimizer
- 2 learning rate=0.0001
- 3 cost function is Mean Square Error



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

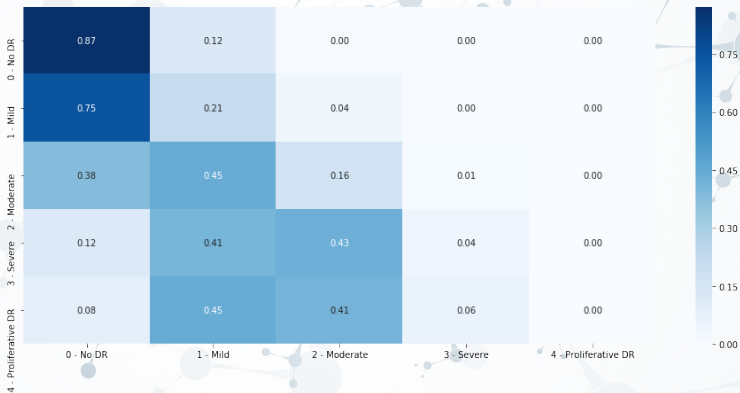
Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

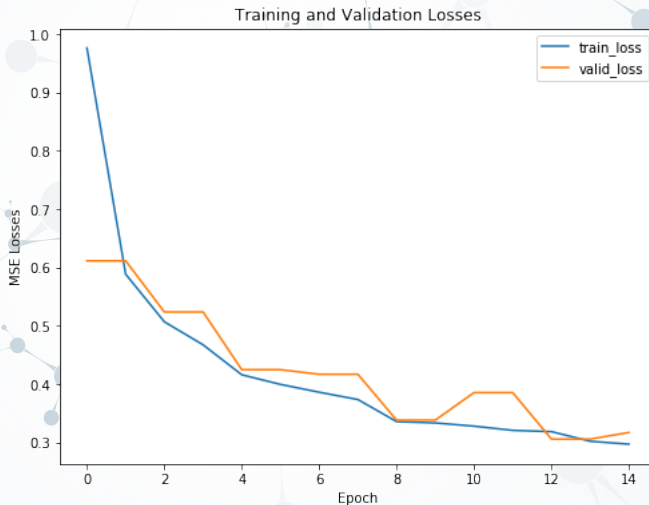
Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

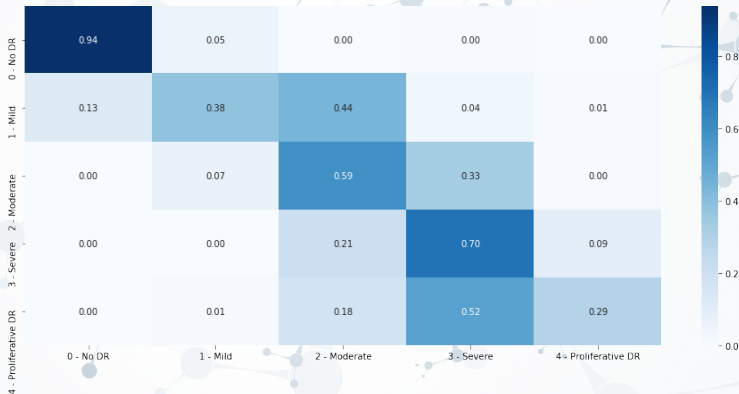
Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

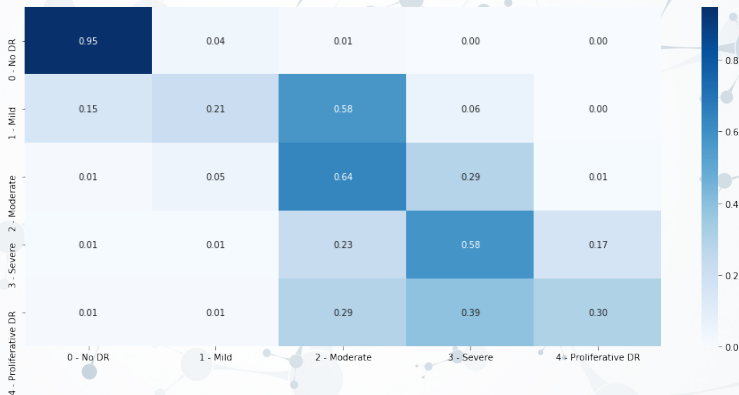
Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

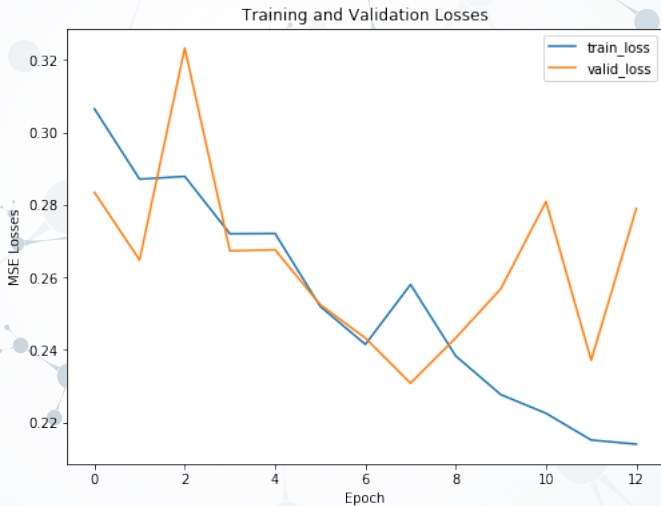
Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

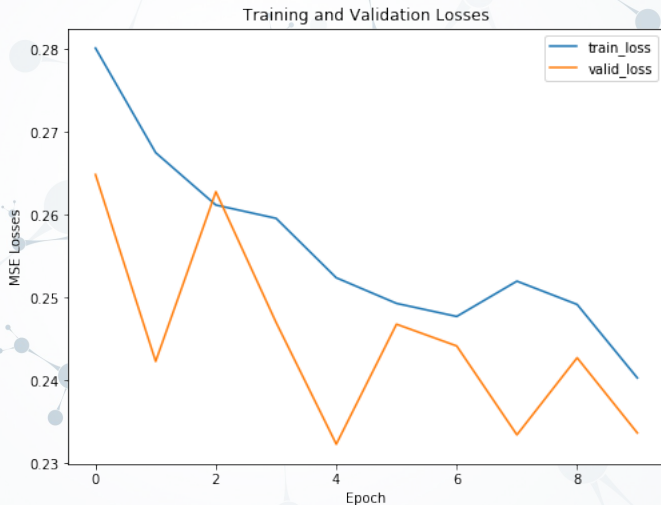
Training and
Finetuning

Result

Deficiency

Improvement

References





Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References





*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

- 1) This model is very slow .Without GPU it takes more than 5 minutes to predict single image



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

- 1) This model is very slow .Without GPU it takes more than 5 minutes to predict single image
- 2) This model is very big .It is almost 2 GB in size.Which makes it impossible for Deployment



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

- 1) This model is very slow .Without GPU it takes more than 5 minutes to predict single image
- 2) This model is very big .It is almost 2 GB in size.Which makes it impossible for Deployment



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

1) for pre-trained model we can use something like efficient-net which is significantly smaller



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

- 1) for pre-trained model we can use something like efficient-net which is significantly smaller
- 2) We can use Heat-Map of model and overlay it on the top of existing picture to help human experts to conclude



*Detecting Diabetic
Retinopathy using Deep
Learning*

Introduction

*Convolutional
Neural Network*

*Transfer
Learning*

Data

*Training and
Finetuning*

Result

Deficiency

Improvement

References

- 1) for pre-trained model we can use something like efficient-net which is significantly smaller
- 2) We can use Heat-Map of model and overlay it on the top of existing picture to help human experts to conclude



Detecting Diabetic
Retinopathy using Deep
Learning

Introduction

Convolutional
Neural Network

Transfer
Learning

Data

Training and
Finetuning

Result

Deficiency

Improvement

References

- 1 **Preprocessing the Image**
[https://www.kaggle.com/ratthachat/
aptos-eye-preprocessing-in-diabetic-retinopat](https://www.kaggle.com/ratthachat/aptos-eye-preprocessing-in-diabetic-retinopat)
- 2 **Dataset** [https://www.kaggle.com/c/
aptos2019-blindness-detection](https://www.kaggle.com/c/aptos2019-blindness-detection)
- 3 **Gradient Descent** [https://towardsdatascience.com/
understanding-the-mathematics-behind-gradient](https://towardsdatascience.com/understanding-the-mathematics-behind-gradient)
- 4 **Transfer Learning** [https://towardsdatascience.com/
what-is-transfer-learning-8b1a0fa42b4](https://towardsdatascience.com/what-is-transfer-learning-8b1a0fa42b4)
- 5 **ReNext**
<https://github.com/facebookresearch/ResNeXt>