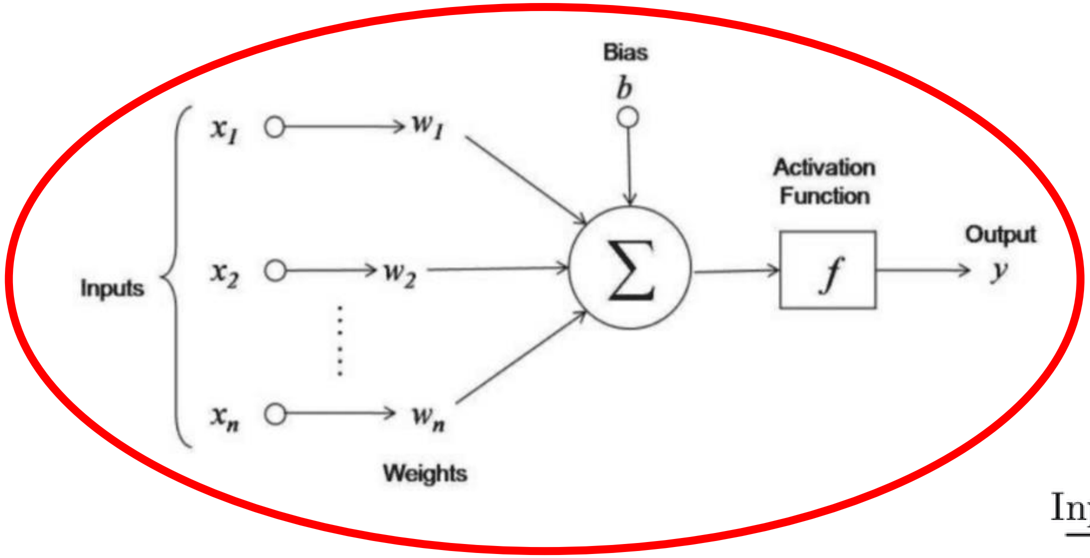
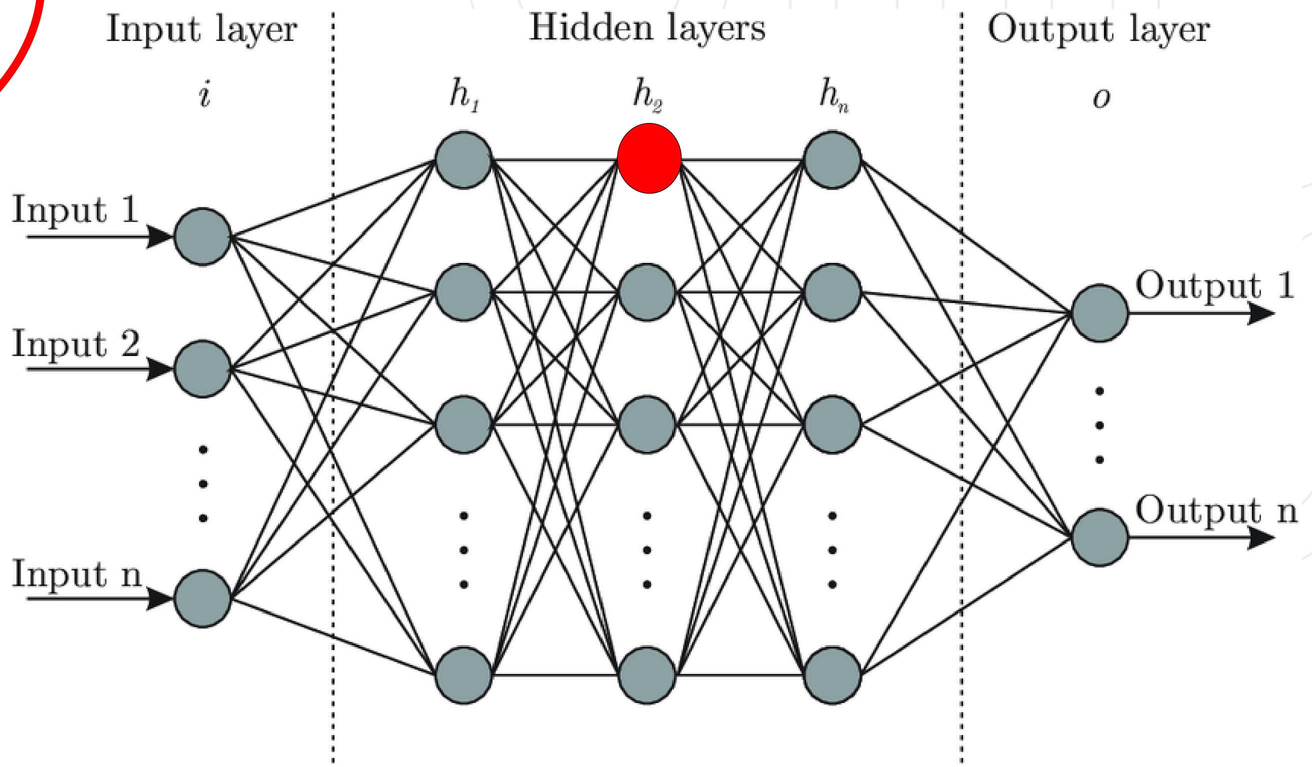
Demonstrating the benefits of **transfer learning** when grading diabetic retinopathy in fundus photographs with deep learning

Adam Hulman (@adamhulman)

Neural networks & deep learning





https://dimensionless.in/artificial-intelligence-accelerate-the-power-with-neural-networks
https://ai.plainenglish.io/my-notes-on-neural-networks-adf3e49657f8

Deep Residual Learning for Image Recognition

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Microsoft Research
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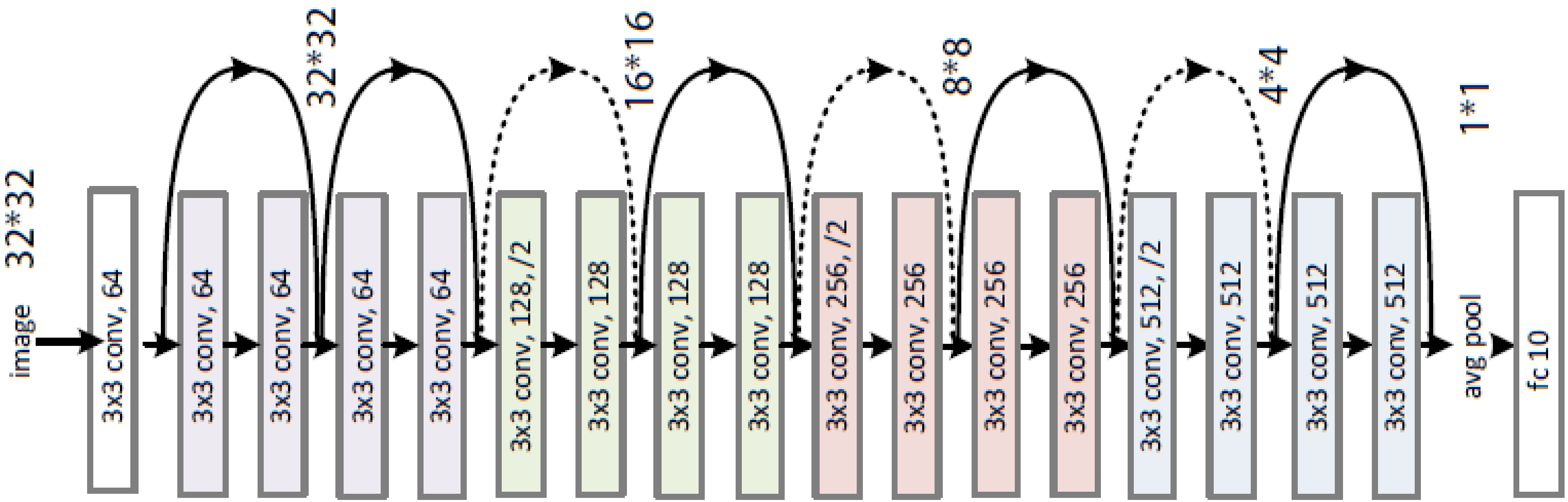

www.programmersought.com/article/68543552068/

ImageNet: A Large-Scale Hierarchical Image Database

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li and Li Fei-Fei
Dept. of Computer Science, Princeton University, USA
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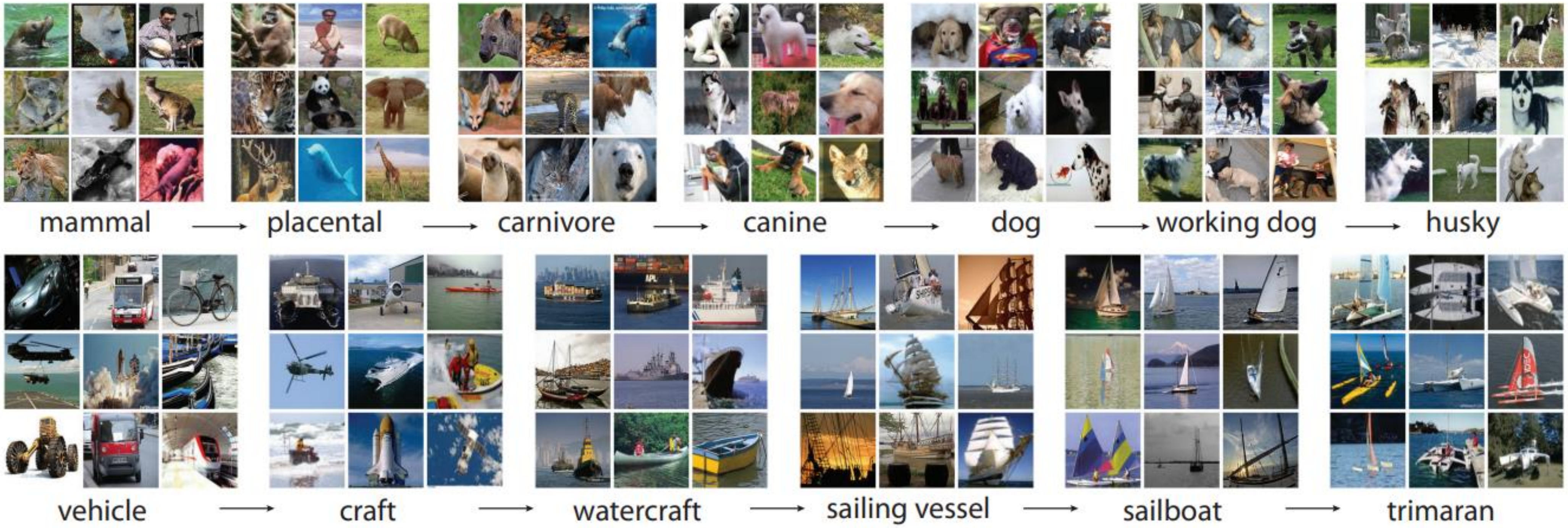
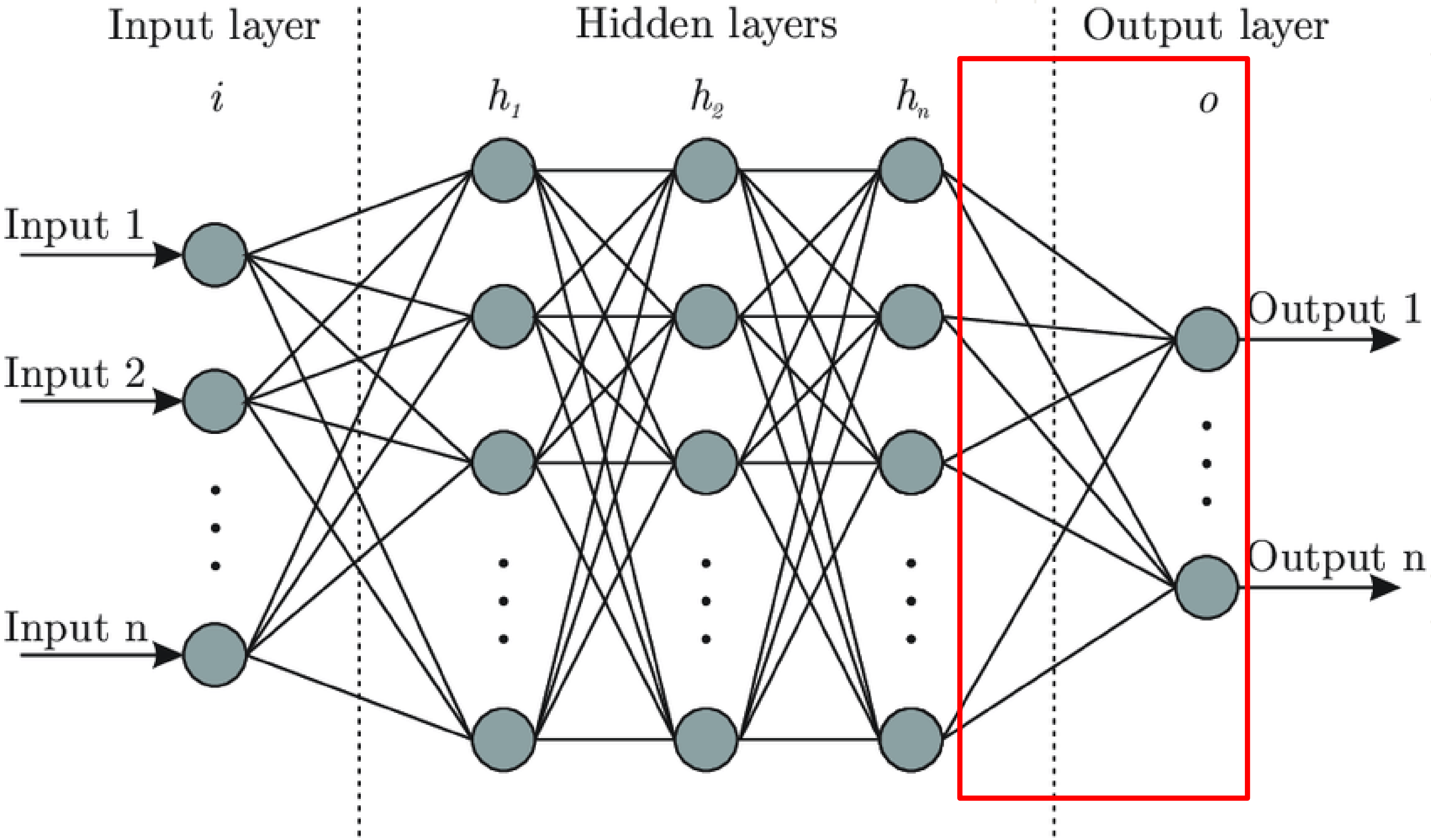


Figure 1: A snapshot of two root-to-leaf branches of ImageNet: the **top** row is from the mammal subtree; the **bottom** row is from the vehicle subtree. For each synset, 9 randomly sampled images are presented.

https://ieeexplore.ieee.org/document/5206848

Using a pre-trained model for a task different to what it was originally trained for is known as **transfer learning**.

Lesson 1 – fast.ai course on deep learning



1. Replace and fine-tuning the last layer
2. Train the whole network

Visualizing and Understanding Convolutional Networks

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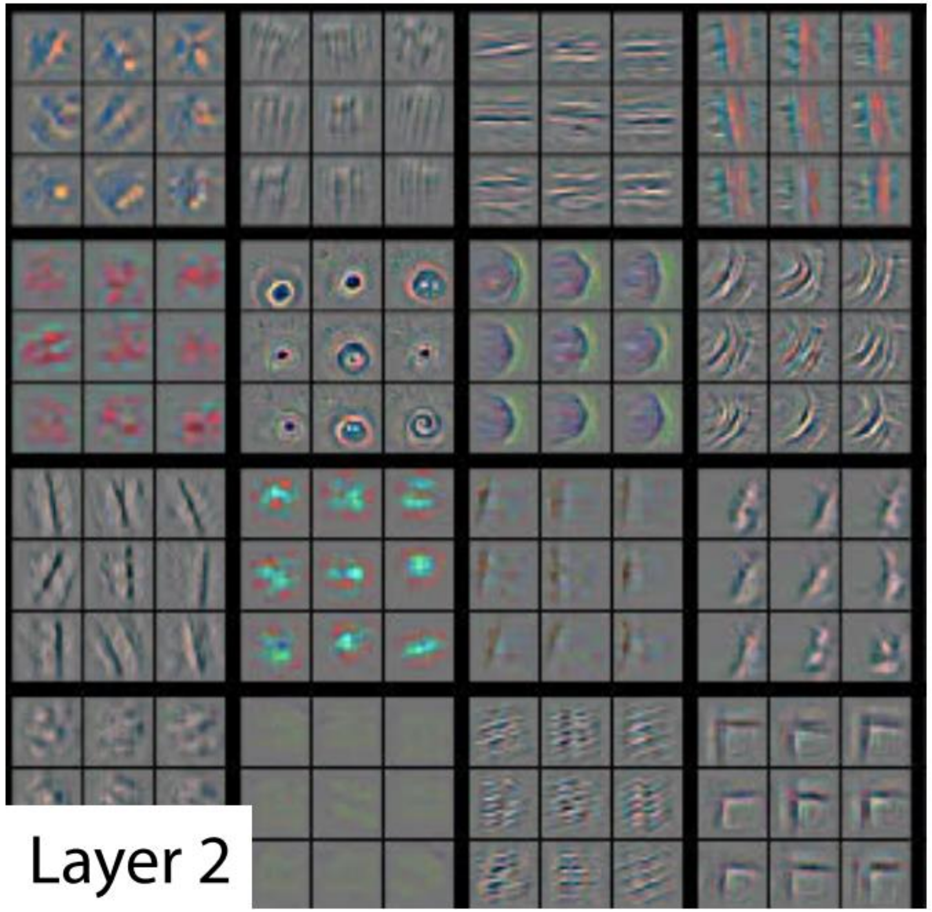
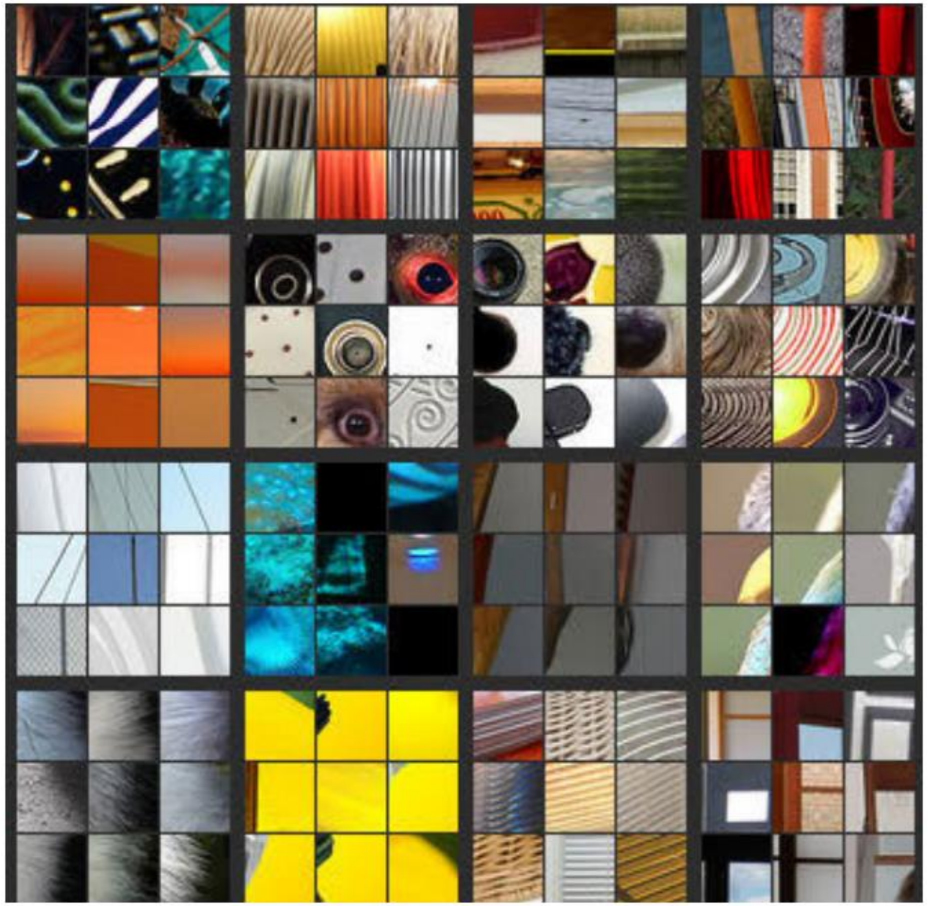
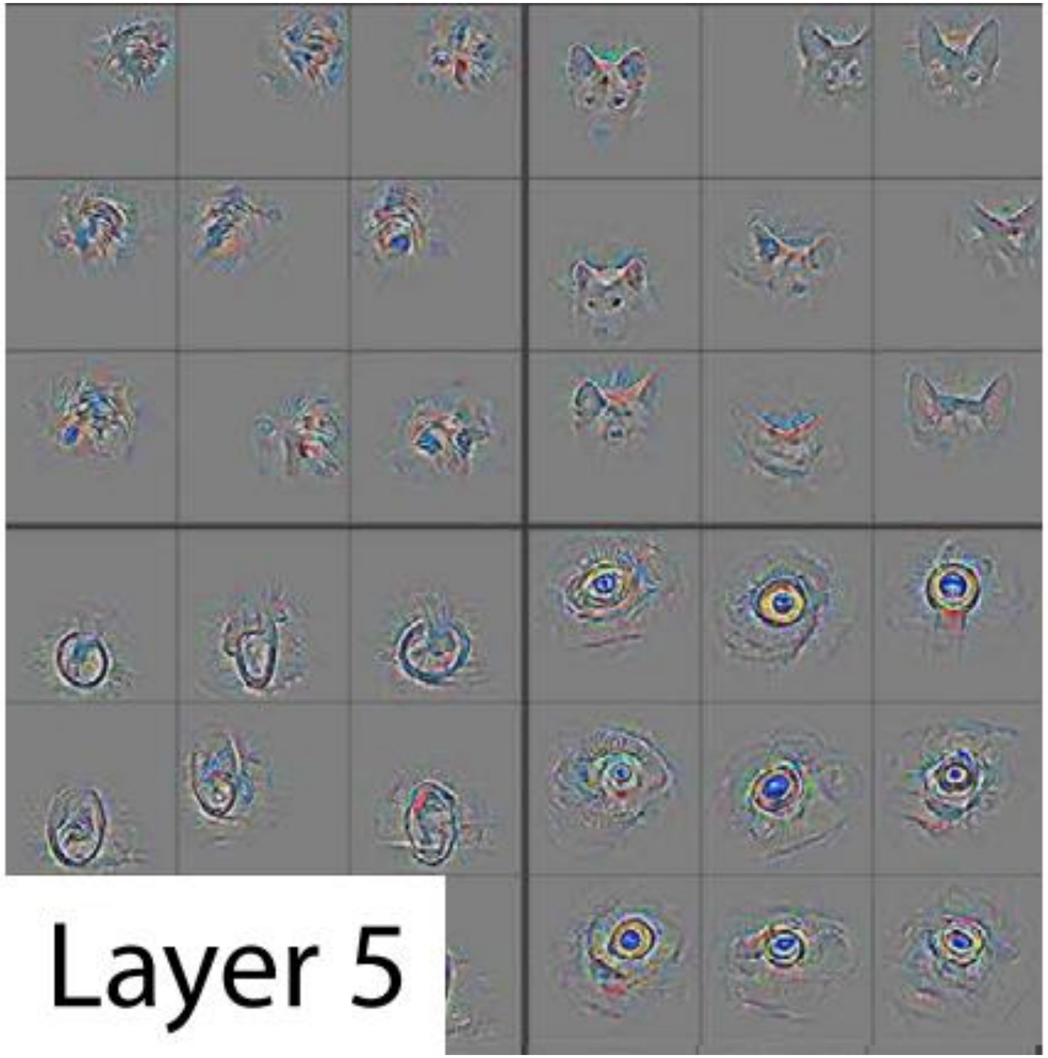
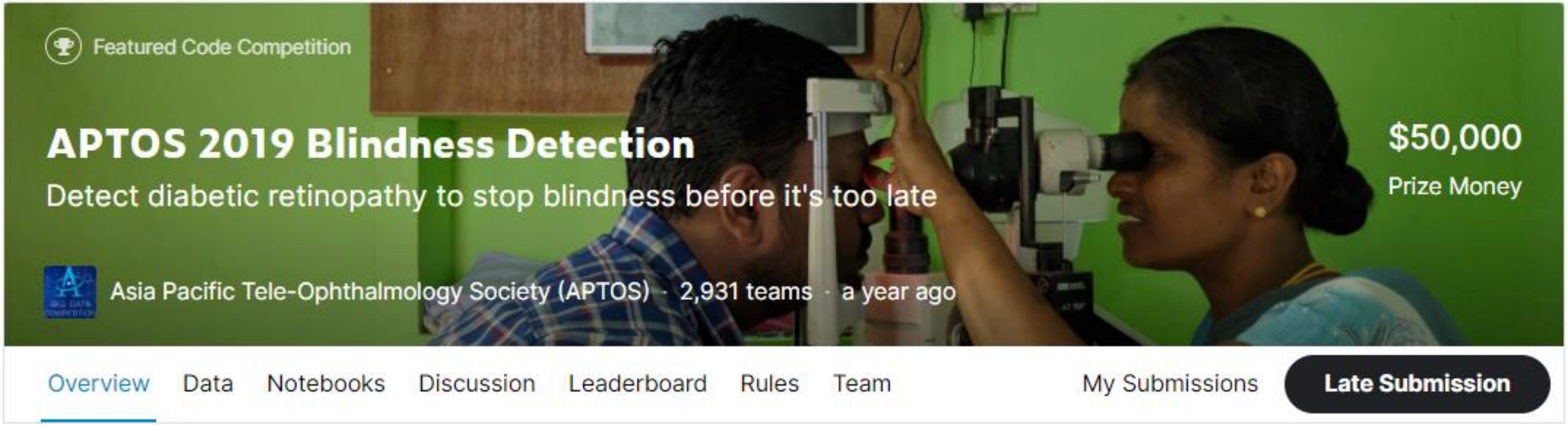
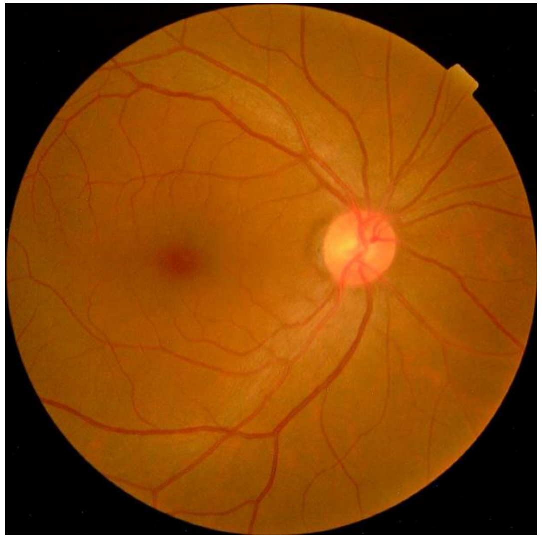


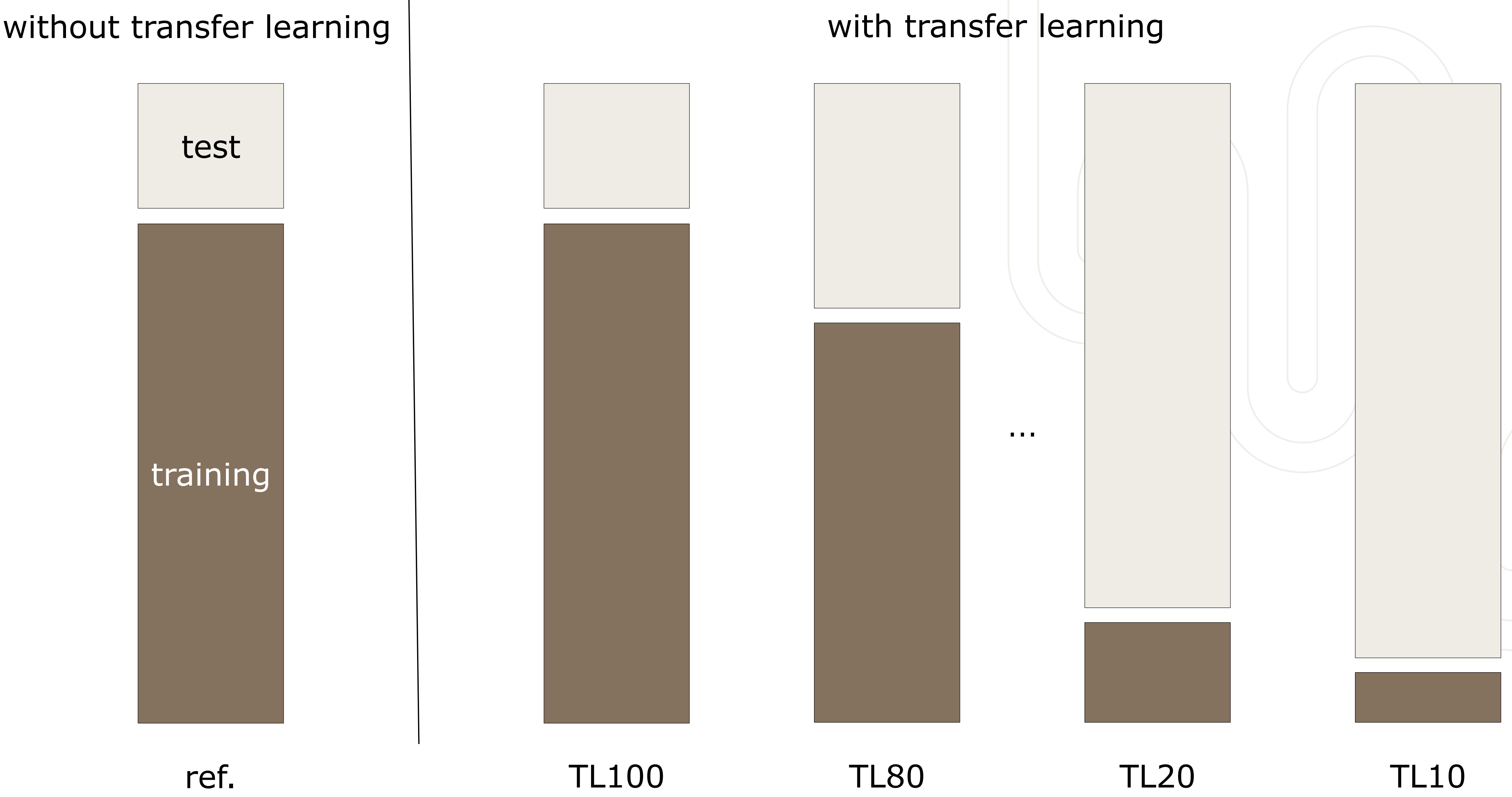



Layer 5





Target/outcome	
0	No diabetic retinopathy
1	Mild
2	Moderate
3	Severe
4	Proliferate


without transfer learning
with transfer learning
test
training
...
ref.
TL100
TL80
TL20
TL10

Model	Accuracy (%)	Kappa	Cross-entropy*
Ref.	72	0.74	0.79
TL100	82	0.89	0.62
TL80	81	0.87	0.62
TL60	80	0.86	0.66
TL40	78	0.83	0.74
TL20	75	0.80	0.88
TL10	73	0.79	0.95

*the lower the better

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Convolutional Neural Networks for Diabetic Retinopathy

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Abstract

The diagnosis of diabetic retinopathy (DR) through colour fundus images requires experienced clinicians to identify the presence and significance of many small features which, along with a complex grading system, makes this a difficult and time consuming task. In this paper, we propose a CNN approach to diagnosing DR from digital fundus images and accurately classifying its severity. We develop a network with CNN architecture and data augmentation which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and haemorrhages on the retina and consequently provide a diagnosis automatically and without user input. We train this network using a high-end graphics processor unit (GPU) on the publicly available Kaggle dataset and demonstrate impressive results, particularly for a high-level classification task. On the data set of 80,000 images used our proposed CNN achieves a sensitivity of 95% and an accuracy of 75% on 5,000 validation images.

Peer-review under responsibility of the Organizing Committee of MIUA 2016

Keywords: Deep Learning, Convolutional Neural Networks, Diabetic Retinopathy, Image Classification, Diabetes

1. Introduction

Diabetic Retinopathy (DR) is one of the major causes of blindness in the western world[1,2]. Increasing life expectancy, indulgent lifestyles and other contributing factors mean the number of people with diabetes is projected to continue rising[3]. Regular screening of diabetic patients for DR has been shown to be a cost-effective and important aspect of their care[4]. The accuracy and timing of this care is of significant importance to both the cost and effectiveness of treatment. If detected early enough, effective treatment of DR is available, making this a vital process[5].

Classification of DR involves the weighting of numerous features and the location of such features[6]. This is highly time consuming for clinicians. Computers are able to obtain much quicker classifications once trained, giving the ability to aid clinicians in real-time classification. The efficacy of automated grading for DR has been an active area

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Diabetic Retinopathy Grading Using ResNet Convolutional Neural Network

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***Abstract*— Designing and developing automated systems to detect and grade Diabetic Retinopathy (DR) is one of the recent research areas in the world of medical image applications since it is considered one of the main causes of total blindness for people who have diabetes in the mid-age. In this paper, a complete pipeline for retinal fundus images processing and analysis has been described, implemented and evaluated. This pipeline has three main stages: (i) image pre-processing, (ii) features extraction and (iii) classification. In the first stage, the image has been pre-processed using different transformations to standardize the images and to enhance the images quality. It has been proven that Gaussian filtering is quite effective in this context to enhance the images contrast. In the second and third stage, the convolution neural network (CNN), one of the best neural network architecture for image analysis applications, has been used. The concept of transfer learning and fine tuning have been advocated in this paper and applied for ResNet18 using the publicly available Kaggle dataset. The problem of DR diagnosis has been handled as a multi-class classification problem where there are five levels of the disease severity (0 – No DR, 1 – Mild, 2 – Moderate, 3 – Severe, 4 – Proliferative DR). The final model has achieved accuracy of 70 %, recall of 50% and specificity of 88% outperforming other models built from scratch with less training time and proving the efficiency of transfer learning in this context. The training process has considered the problem of imbalanced dataset using two different ways and it has been discovered that using imbalanced dataset sampler is a very efficient solution. The final model developed in this research could be used as the main unit for a computer aided system to be hosted online for DR detection and diagnosis.**

Keywords*— *Convolutional Neural Networks, Retinal Fundus Images Classification, Transfer Learning, Diabetic Retinopathy

I. Introduction and Background

Diabetes is a chronic disease causing the sugar (glucose) level in the blood to arrive to dangerous high levels. Insufficient production of insulin or an inability of the body to correctly use insulin causes diabetes. The number of people diagnosed to have diabetes increases over last years. According to International Diabetes Federation (IDF) Atlas 7th edition in 2015 more than 415 million people worldwide are affected by diabetes. Also, According to IDF Western Pacific (WP) Atlas 8th Edition in 2017, there are approximately 158.8 million adults in the age range 20-79 years were living with diabetes in the IDF WP region, representing 9.5% of the population. More than 54% of the cases are without diagnoses. Approximately two thirds of the cases of adults with diabetes in the WP region live in urban areas. In Malaysia, there were over 3.492.600 cases of diabetes in 2017, and the number increases according to the official website of IDF [1].

Diabetic Retinopathy (DR) is a disease infecting the retina of people who have diabetes. The retina is the layer at the back of the eye which mainly contains nerves. This part is responsible for capturing the image and sending this image back to the brain. DR is a dangerous disease which could lead in the worst case to the total blindness. DR disease evolves through time and mainly has two stages. The first stage is called non-proliferative diabetic retinopathy (NPDR) (Refer to Figure I), whereas the second stage is called proliferative diabetic retinopathy (PDR).

Specialists classify the severity into four categories (1 - Mild DR, 2 - Moderate DR, 3 - Severe DR, 4 - Proliferative DR) (Refer to the Figure II). Understanding the retinal fundus images is not an easy task, and it requires a specialist to check these images manually to check if there are any strange spots or signs of DR which makes the processing time consuming even for well-trained doctors [3]. With this hard to be detected, quick to evolve, and slow to be diagnosed disease, the need for an automated system to detect this disease cannot be underestimated.

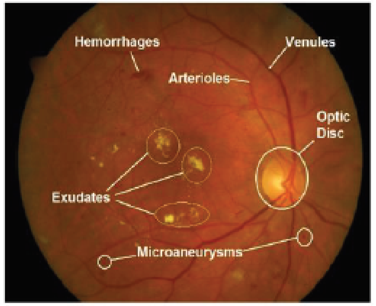

Figure I NPDR Signs on the retina [2]

Using Transfer Learning for Improved Mortality Prediction in a Data-Scarce Hospital Setting

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This performance … corresponds to a **decrease in clinical data collection time from approximately 6 months to less than 10 days**.

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Thank you for your attention!