Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

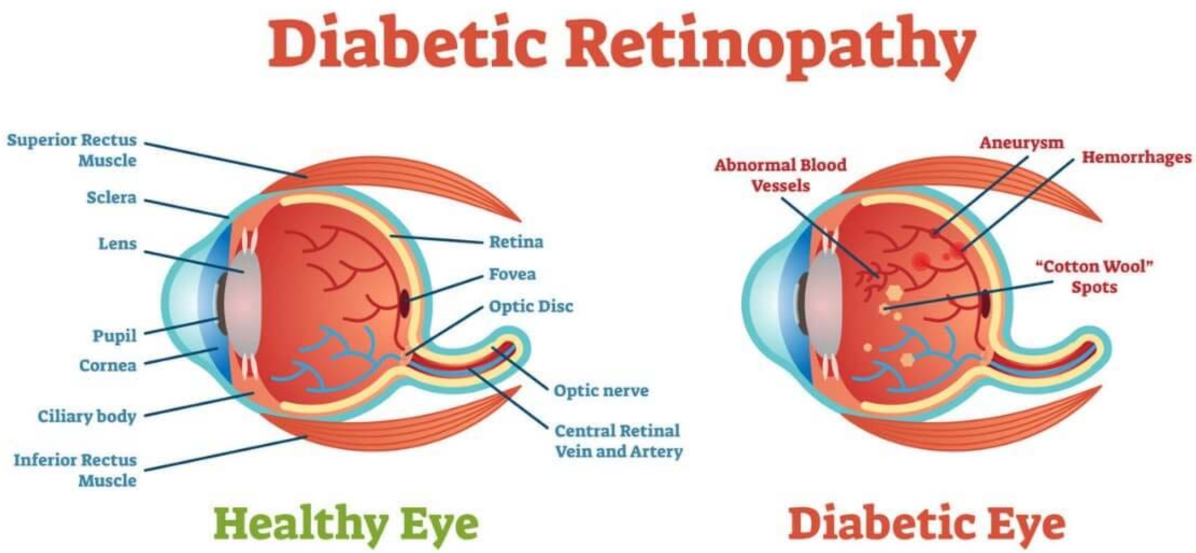
V. Gulshan, L. Peng, M. Coram, et al.

Presentation by Aidan Fitzgerald

What is Diabetic Retinopathy

[1]
"Occurs in 28.5% of people with diabetes in the USA"

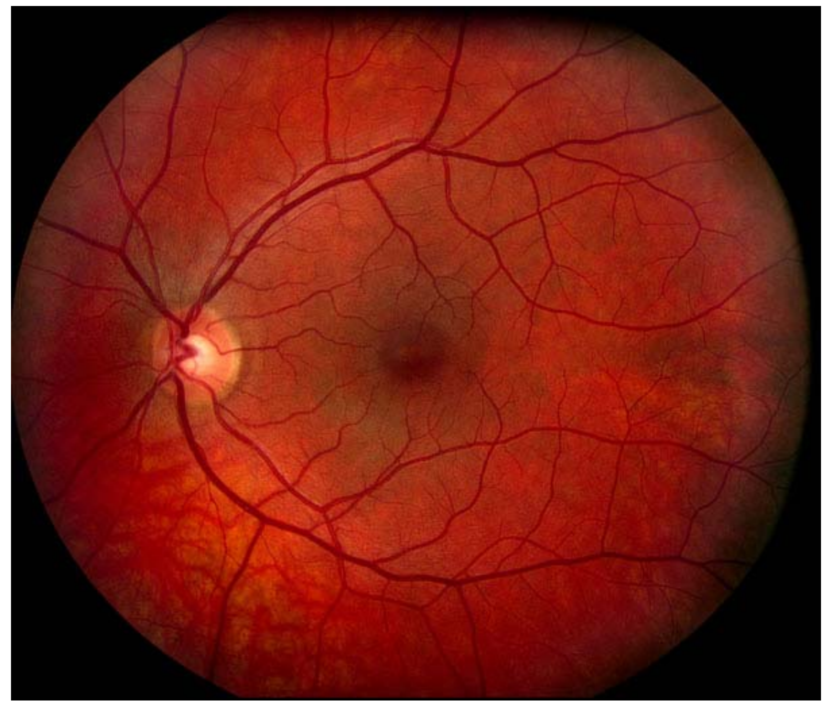
[2]



Retinal Fundus Photographs

- Photograph of the eye
- Used to help detect Diabetic Retinopathy
- Researchers Goal?

[3]



What is the benefit of an automated detection system

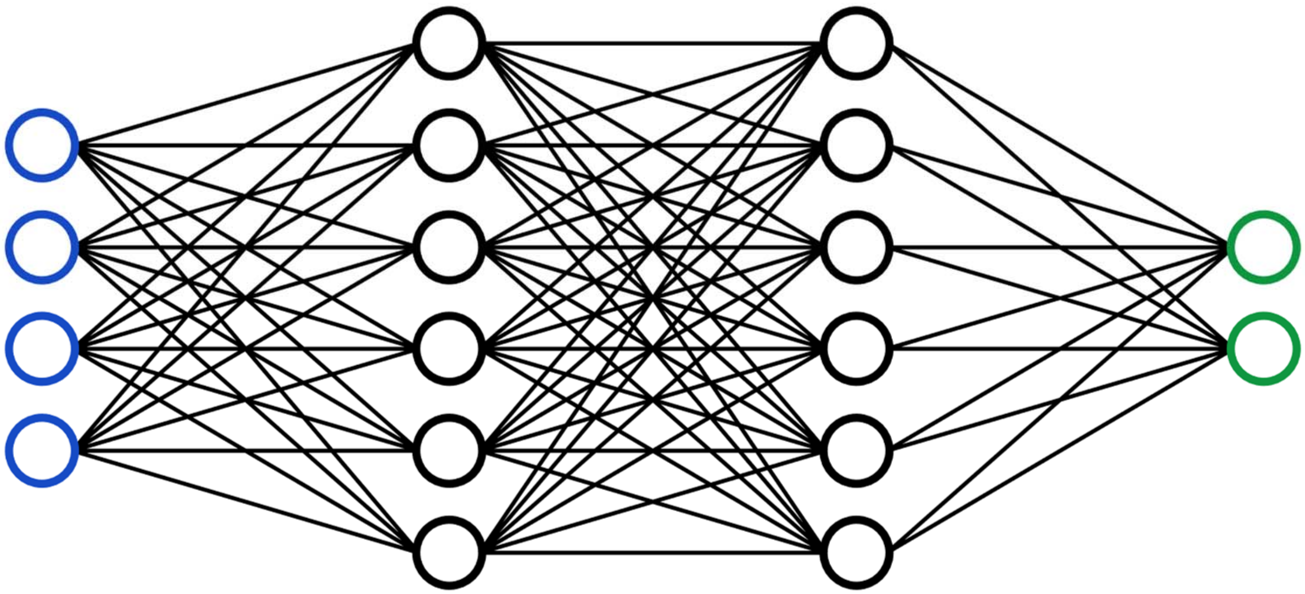
- Manual Interpretation is standard
- Increasing Efficiency
- Reproducibility
- Reducing Barriers to access
- Improving patient outcomes

Machine Learning

- Algorithm for automatic detection is needed
- Machine Learning has been used for classification tasks including diabetic retinopathy
- Previous work has focused on ‘feature engineering’
- Deep learning avoids ‘feature engineering’

Neural Networks

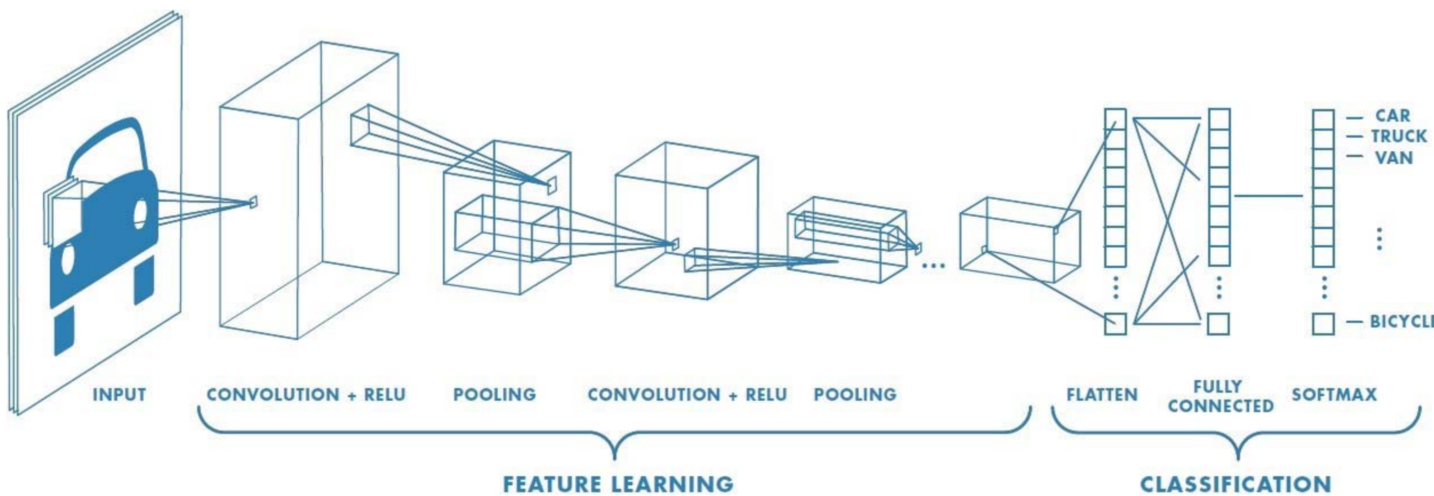
[4]



Convolution Neural Networks

- Good for Image Recognition
- Layers Called Convolutional Layers
- Detects Features of Images

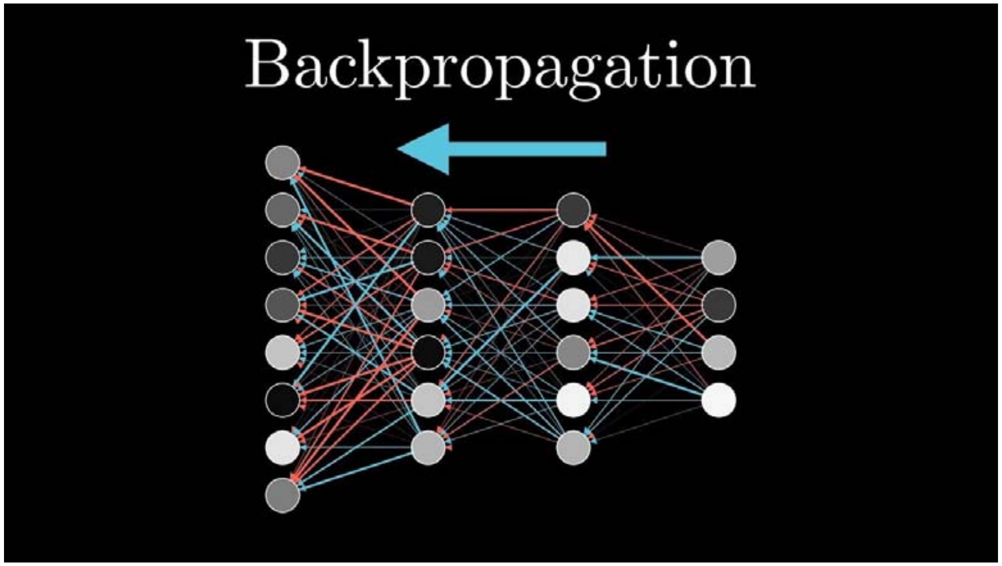
[5]



Back-propagation

- How does the network learn?
- Compares expected output with actual output
- Makes adjustments to weights and biases
- Minimises the cost function

[6]



Data sets

- Trained on 128,175 Retinal Images
- Validated using 2 data sets
- No overlap in the sets
- Diabetic Retinopathy severity was graded into 5 categories

Development of the Algorithm

- Determines diabetic retinopathy severity using the intensities of the pixels
- Parameters are set to random values
- The severity grade is compared to actual grade
- Repeated many times on the data set
- The network was trained to make multiple binary predictions

Evaluation of Algorithm

- Network produced continuous number between 0 and 1 for referable diabetic retinopathy and other classifications
- Specificity and Sensitivity
- Two operating points for the algorithm were selected

Results

- EyePACS-1 validation data set consisted of 9963 images
- Messidor-2 validation data set consisted of 1748 images
- Mean agreement of ophthalmologists on referable diabetic retinopathy images 77.7% and 82.4%
- Mean agreement on non-referable images was 97.4% and 96.3%
- Sensitivity analysis was conducted for several subcategories

Results Cont.

- Sensitivity and specificity at high specificity point 90.3% and 98.1% for first data set
- Sensitivity and specificity at high specificity point 87.0% and 98.5% for second data set
- Sensitivity and specificity at high sensitivity point 97.5% and 93.4% for first data set
- Sensitivity and specificity at high sensitivity point 96.1% and 93.9% for second data set

Results Cont.

- Multiple other networks were trained
- Effect of data set size on performance plateaued at 60 000 images
- Increasing number of grades did not increase performance
- One grade per image on tuning set lead to 36% decrease

Discussion

- Deep neural networks can be trained using large data sets without specifying features for diabetic retinopathy
- Automated system for detection of diabetic retinopathy provides multiple advantages
- Abramof et al[7] achieved a sensitivity of 96.8% and specificity of 59.4%
- Solanki et al[8] achieved a sensitivity of 93.8% and specificity of 72.2%
- Philip et al[9] achieved a sensitivity of 82.6% and a specificity of 76.8%

Discussion cont.

- High sensitivity and specificity is essential
- Researchers determined future medical using deep learning has 2 prerequisites
- There a limitations to the algorithm
- We don’t know what features the algorithm is using to detect diabetic retinopathy
- Algorithm is not a replacement for an eye examination

What's Next....

- Further validation of the algorithm with different with different graders
- Further research is needed to determine possibility of applying this algorithm to a clinical setting
- Machine learning in ophthalmology[7]

References

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