Predicting outcomes in neovascular Age-related Macular Degeneration from retinal images using a convolutional neural network

*****

Supervisors:

Clinical: *****

Machine Learning: *****

Outline

1. Introduction & Background
2. Research aim
3. Literature Review
4. Data & Domain
5. Methodology
6. Results
7. Discussion
8. Conclusion & Future Work

What is AMD?

Age-related Macular Degeneration

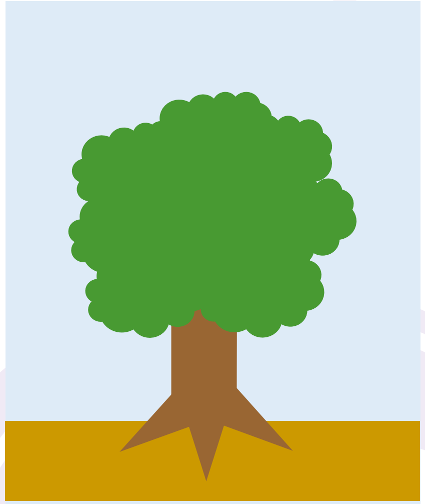
A Leading Cause of Vision Loss

- Can lead to severe vision impairment
- Affects mainly elderly people

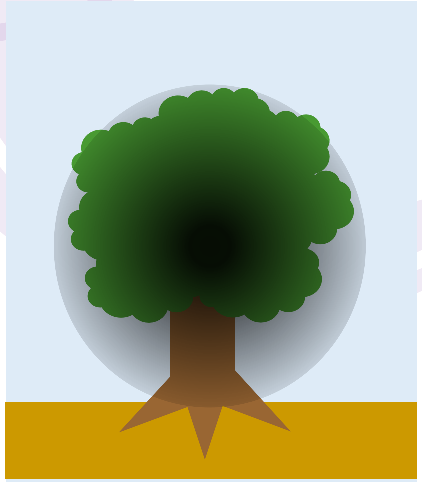
Rising Cases with an Ageing Population

- More AMD cases expected as people live longer
- Early diagnosis & effective treatment are crucial

Normal Vision



Vision in nAMD



AMD types

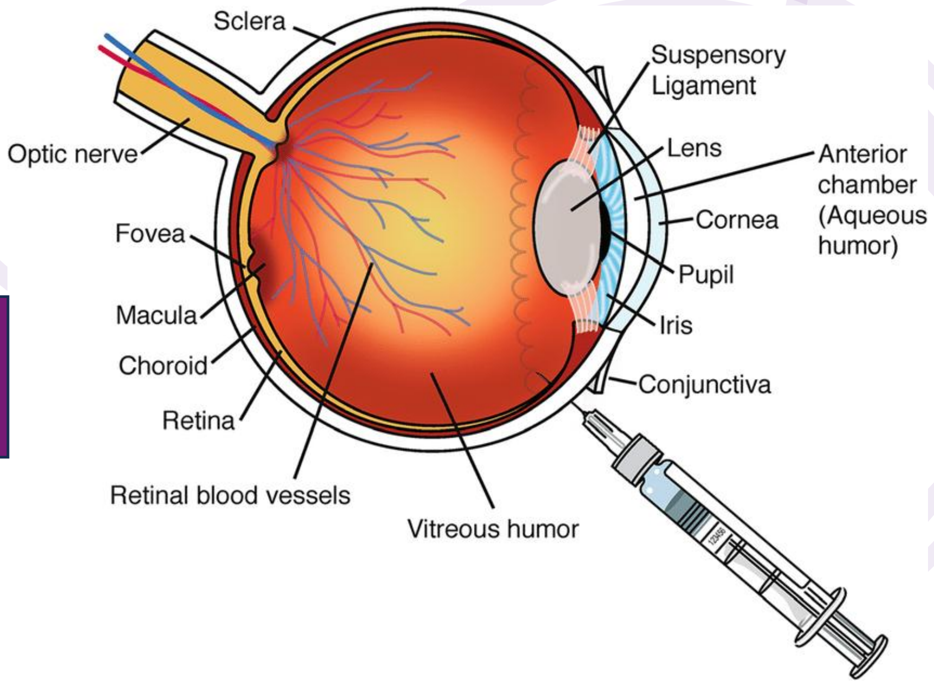
Dry AMD

- More common
- Slower progression
- No effective treatment currently

Wet AMD

- Less common but more severe
- Characterised by **abnormal blood vessel growth**
- **Treatable** with **anti-VEGF** injections

OCT Images



"Fig. 1. Illustration of the ocular anatomy and intravitreal injection...," n.d.

Optical Coherence Tomography (OCT) Scan

- Non-invasive imaging technique
- Produces high-resolution **cross-sectional** images of the retina
- Helps **visualise retinal layers**, fluid accumulation, and biomarkers relevant to AMD

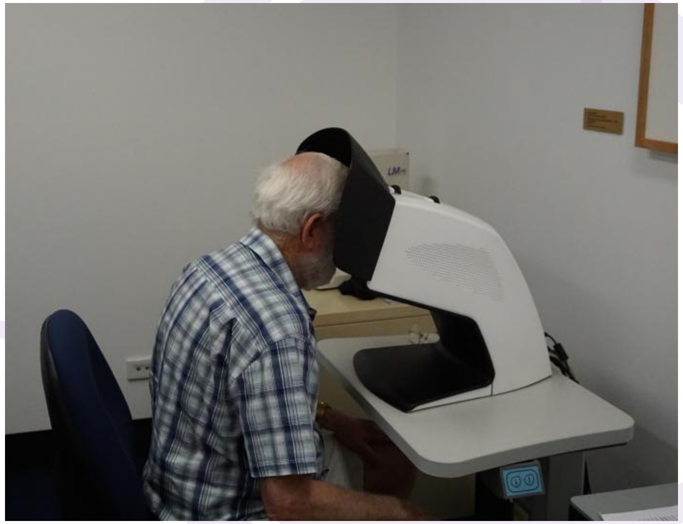


Image credit: spelio, Flickr (CC BY 2.0)
https://www.flickr.com/photos/spelio/49526627638

What does an OCT scan look like?

- Shows retinal layers in detail
- Key tool for detecting abnormalities

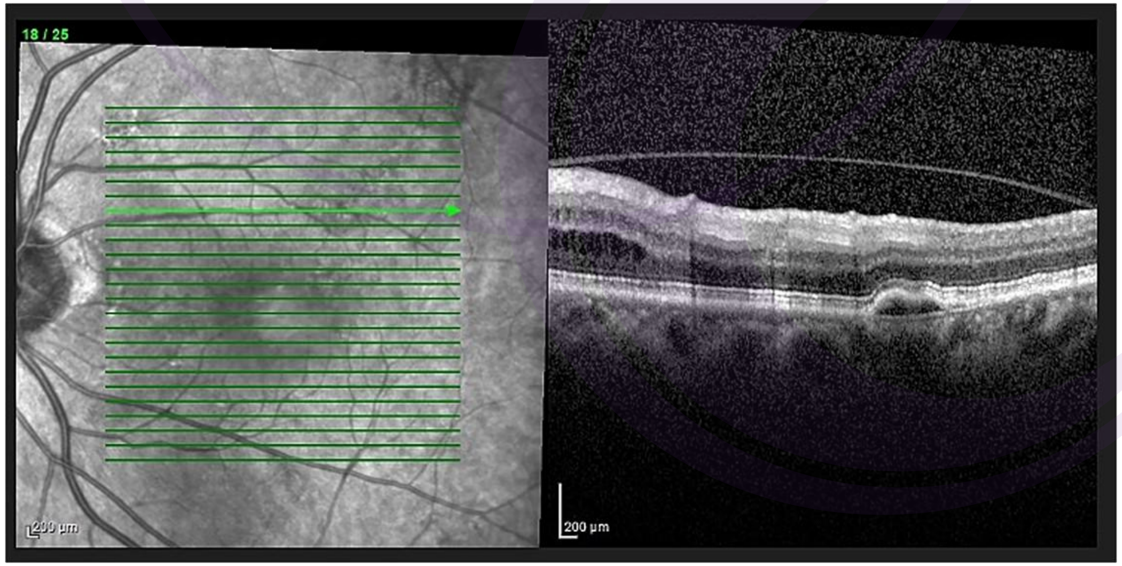


Figure2. "Figure 3 OCT of left eye – showing IRF... | Oxford Academic," n.d

Patients Often Ask

- **How many injections** will they need?
- Will they still be able to **drive** in a year?

To Address These Questions

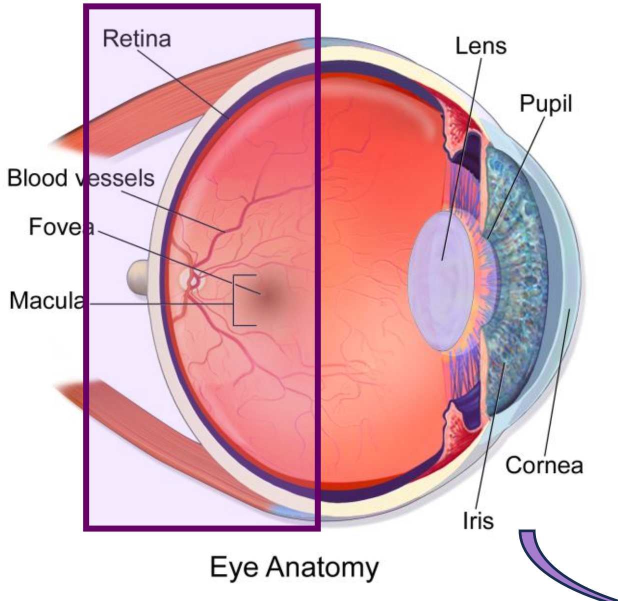
- Can a deep learning model based on baseline OCT images predict **injection frequency** over 12 months?

- Can it predict **future visual acuity** (e.g., driving ability)?

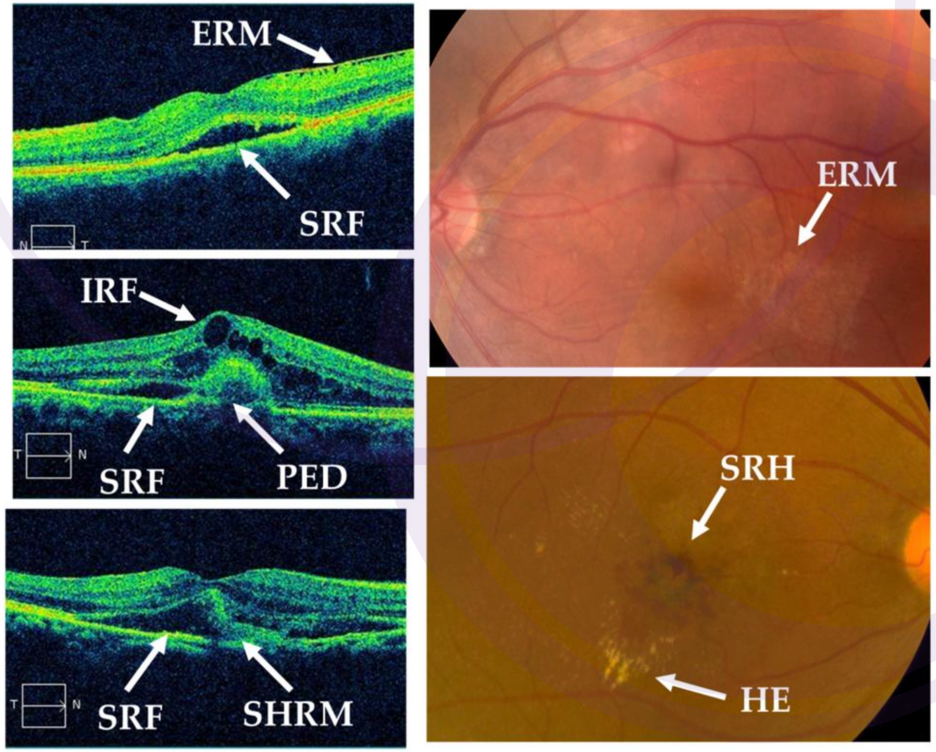
How to predict?

Key Biomarkers - Features linked to disease

- **IRF** (Intraretinal **Fluid**), **SRF** (Subretinal **Fluid**)
- **SHRM** (Subretinal Hyperreflective Material)
- **PED** (Pigment Epithelial Detachment)



Eye Anatomy



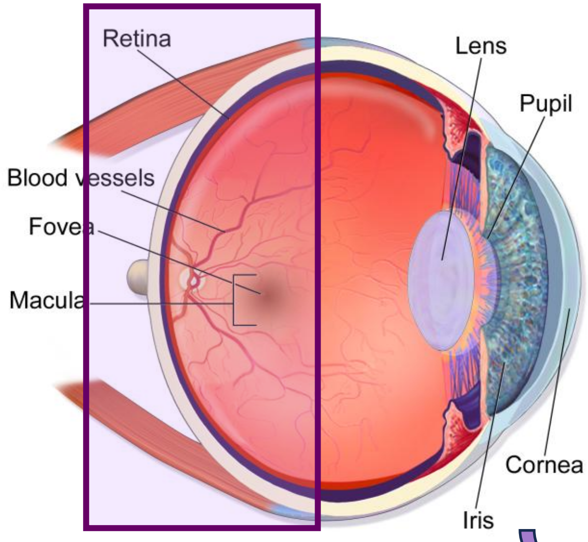
"jcm-13-06244-g001.png," n.d.

Eye Anatomy. Image by Blausen.com staff, 2014, used under CC BY 3.0 License. Available at: https://commons.wikimedia.org/wiki/File:Blausen_0389_EyeAnatomy_02.png

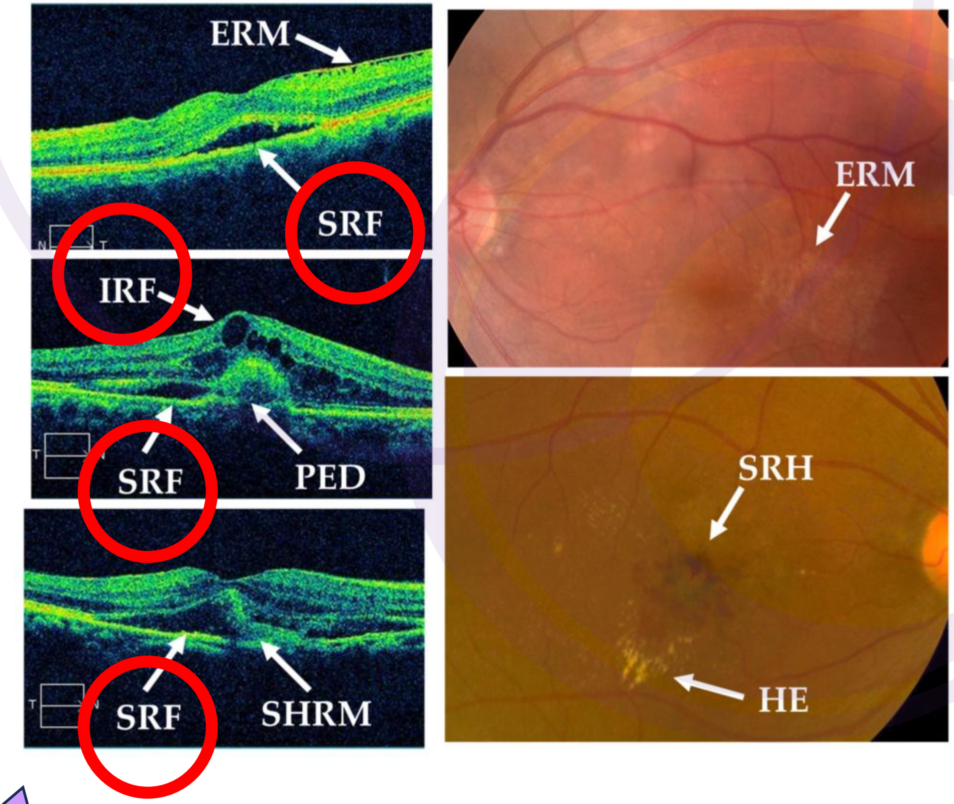
Key Biomarkers

- **IRF** (Intraretinal **Fluid**), **SRF** (Subretinal **Fluid**)
- SHRM (Subretinal Hyperreflective Material)
- PED (Pigment Epithelial Detachment)

Fluid - low signals



Eye Anatomy

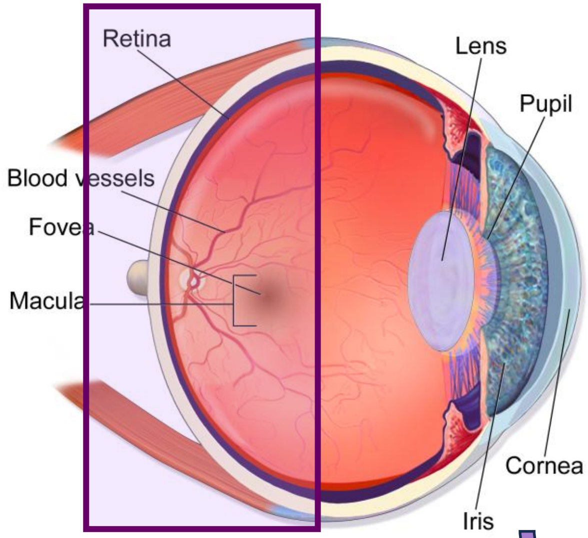


“jcm-13-06244-g001.png,” n.d.

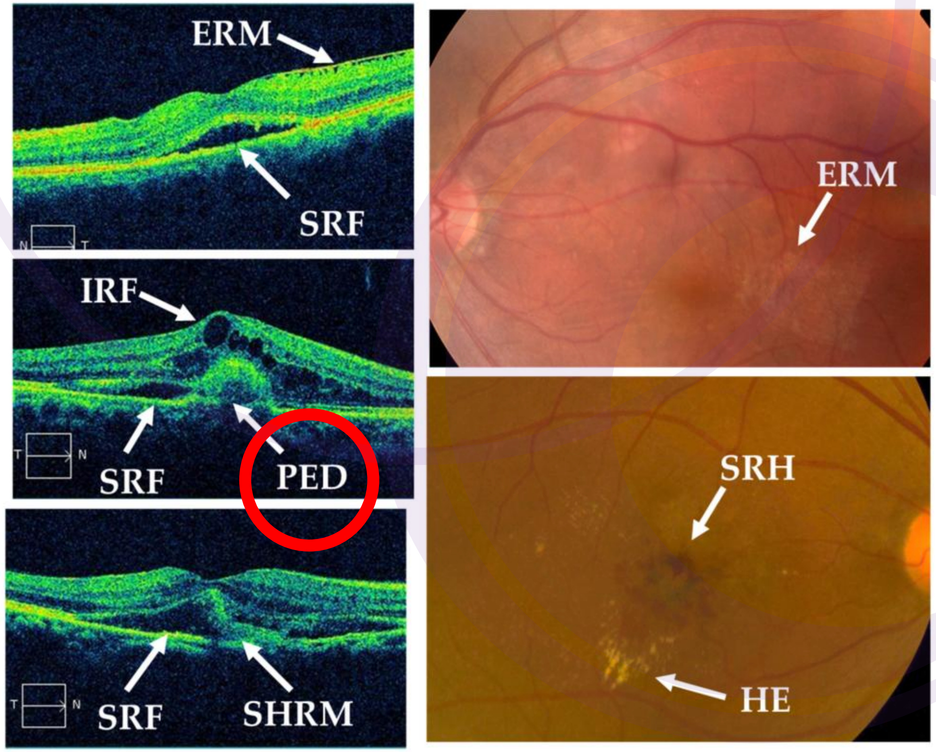
1-2. Key Biomarkers

The retinal pigment layer separates from the tissue below

- **IRF** (Intraretinal **Fluid**), **SRF** (Subretinal **Fluid**)
- **PED** (Pigment Epithelial Detachment)
- **SHRM** (Subretinal Hyperreflective Material)



Eye Anatomy



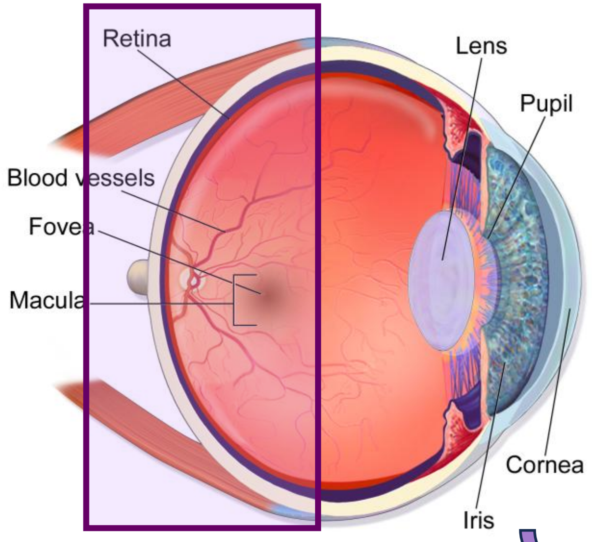
“jcm-13-06244-g001.png,” n.d.

Eye Anatomy. Image by Blausen.com staff, 2014, used under CC BY 3.0 License. Available at: https://commons.wikimedia.org/wiki/File:Blausen_0389_EyeAnatomy_02.png

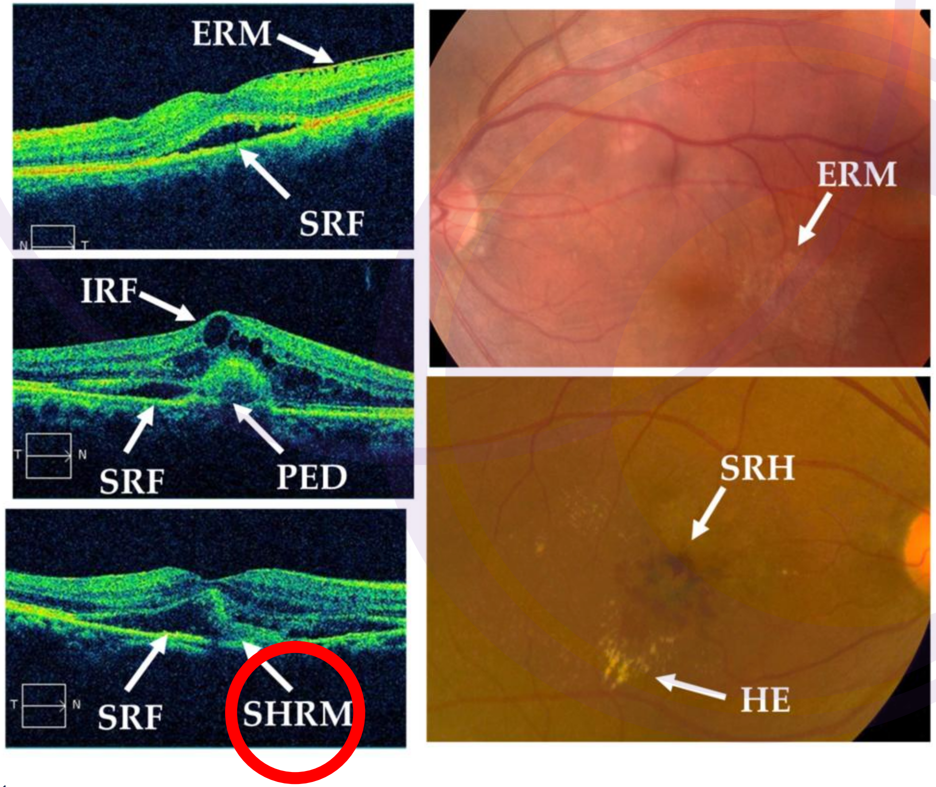
1-2. Key Biomarkers

bright, solid-looking material under the retina

- IRF (Intraretinal Fluid), SRF (Subretinal Fluid)
- PED (Pigment Epithelial Detachment)
- **SHRM** (Subretinal Hyperreflective Material)



Eye Anatomy



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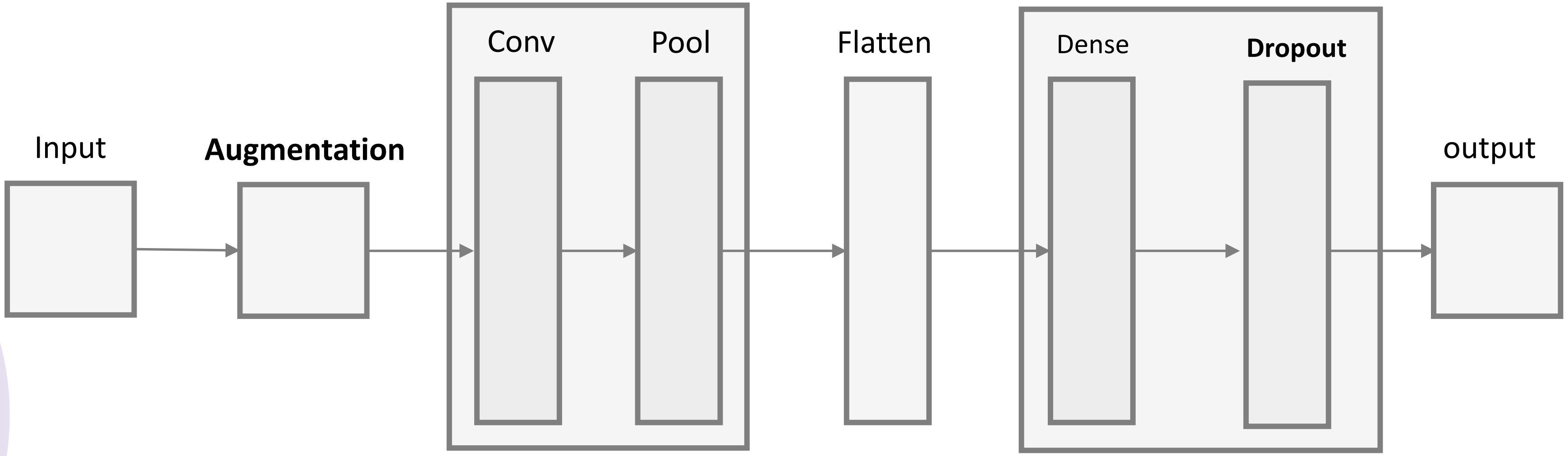
Eye Anatomy. Image by Blausen.com staff, 2014, used under CC BY 3.0 License. Available at: https://commons.wikimedia.org/wiki/File:Blausen_0389_EyeAnatomy_02.png

What are Convolutional Neural Networks (CNNs)?

- CNNs extract **image features** hierarchically.
- Construct of convolution, ReLU activation, pooling, and fully connected layers.
- In ophthalmology, CNNs detect fluid and classify AMD stages.



Prior Work

- AI in medical imaging improves diagnosis and efficiency.

- In ophthalmology, CNNs detect fluid and classify disease stages in OCT.

Existing models:

- RETFluidNet, Vienna Fluid Monitor, Deep Sequence, 3D U-Net.
- Strong performance in segmentation and risk stratification.

Prior Work

- Prior CNNs focus on **image-level tasks** (fluid detection, disease staging).
- They **do not predict clinical outcomes** (e.g., treatment count, visual acuity).
- This dissertation explores **outcome prediction**, aiming for direct clinical relevance.

Data & Domain

- OCT scans from the Heidelberg Spectralis system

- **15** cases' OCT scans with nAMD (wet AMD) from **6** NHS clinics across the UK

→Multi-site data ensures diversity in imaging and clinical cases

Dataset & Preprocessing

1. Selected **14** patients' data out of 15
(clinician decision – poor-quality scan excluded)

15 patients

(1 excluded by ophthalmologist)

14 patients

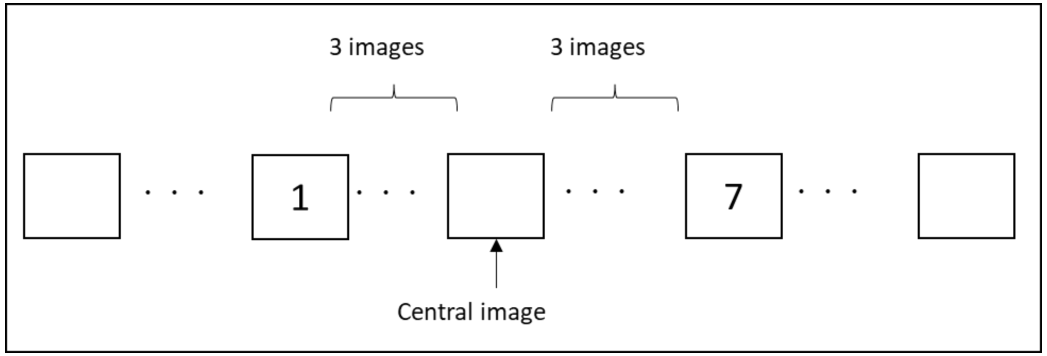
(each with 14–93 slices)

Central slice selected per patient

±3 slices chosen (7 total per patient)

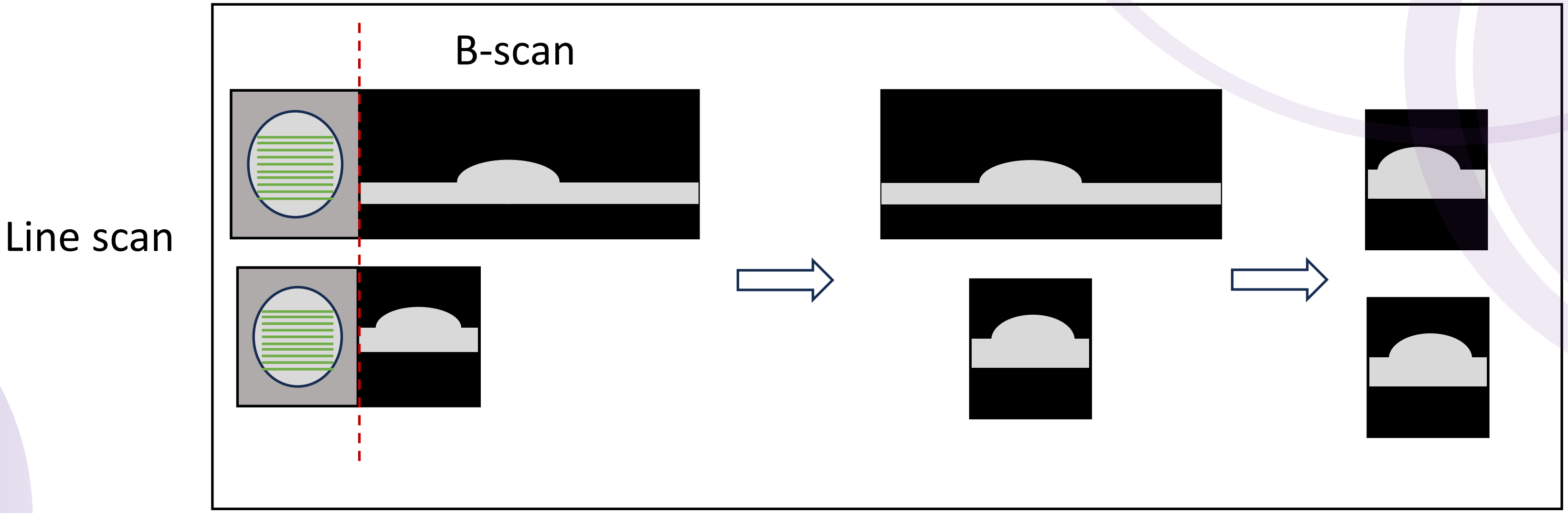
Final dataset: 14 patients × 7 slices = 98 OCT images

2. Selected **7** important slices per patient



Dataset & Preprocessing

3. Cropped and resized images to **450** $\times$ **450** pixels



Approaches

How well can a CNN predict Treatment Frequency and Visual Acuity?

Challenges: Limited dataset size

Approaches:

1. **Cross-validation (7 splits)**: Reducing variance and ensuring more **robust** evaluation
2. **Data Augmentation**: Expanding the dataset artificially to **stabilise** training
3. **Transfer Learning**: Leveraging **prior knowledge** from pre-trained models

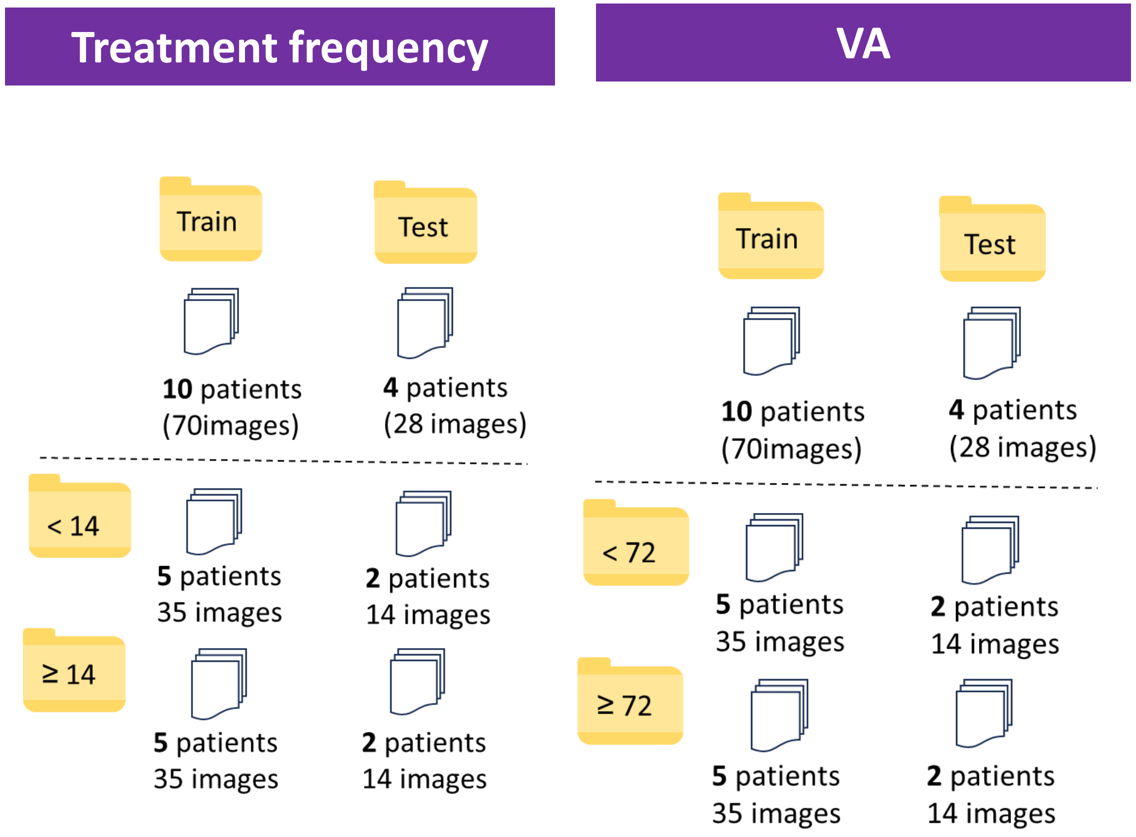
Approach 1 - Data split (Cross-Validation)

Low High

Two groups each:

- Treatment frequency: < **14** or ≥ **14**
- Visual acuity (words) : < **72** or ≥ **72**

- **7**-fold cross-validation with balanced splits.



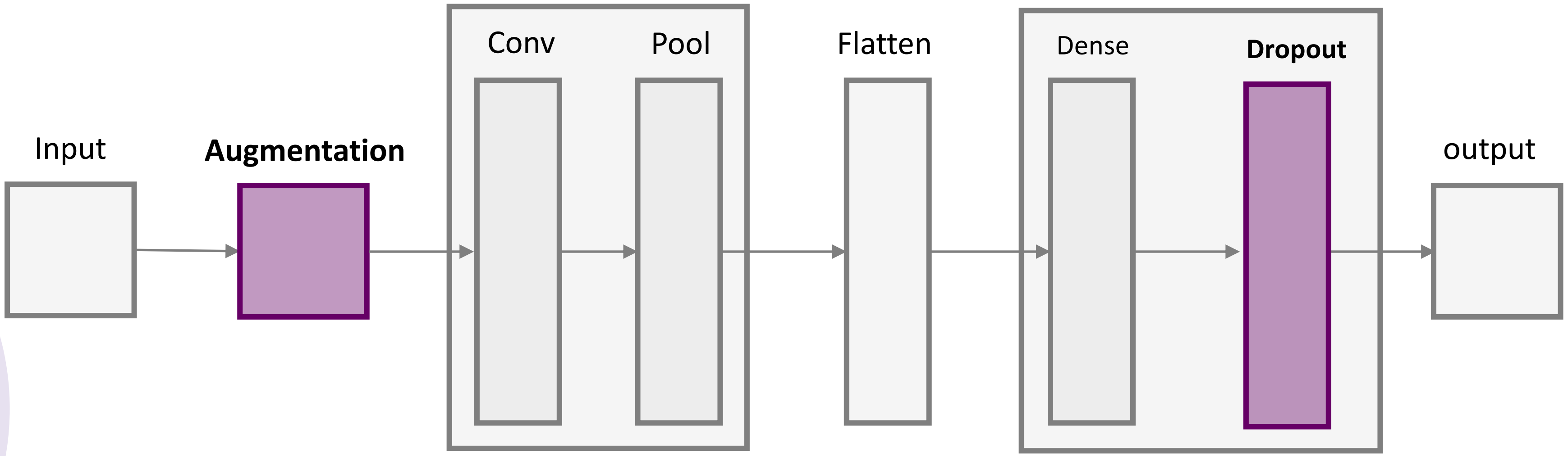
Models

- Preprocessed OCT images
  - Baseline CNN (**No** Augmentation)
  - Baseline CNN (**With** Augmentation)
  - Transfer Learning

Approach 2 - Model Generalisation

Augmentation:
flip, **zoom**, **contrast changes**, **noise** — improves robustness to OCT scan variations

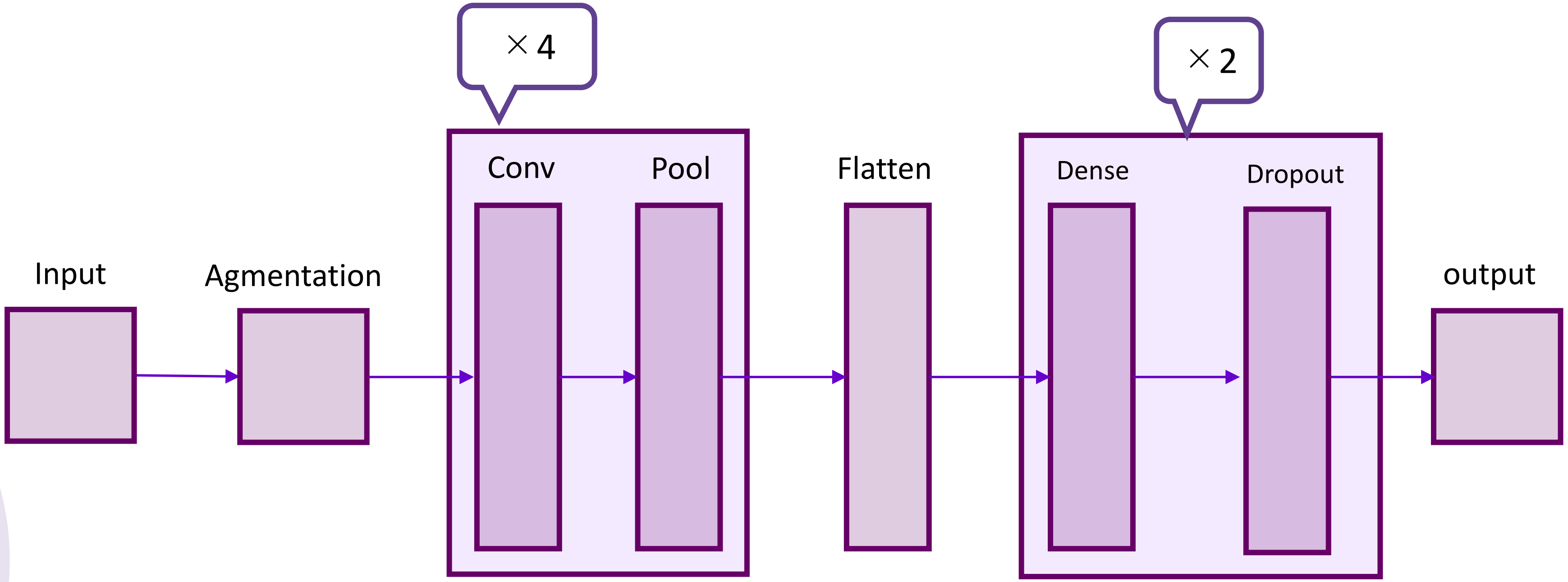
Regularisation:
batch normalisation, dropout layers, early stopping — prevents overfitting



Baseline CNN Model

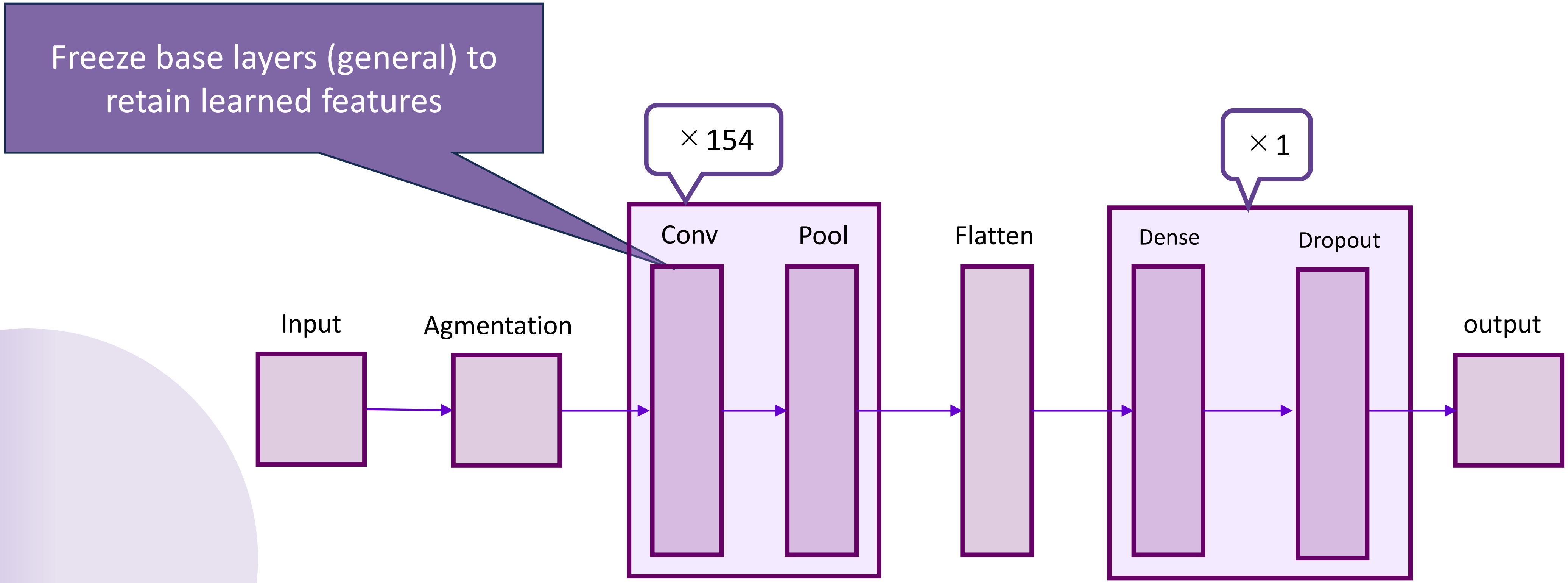
Model Architecture

- 4 convolutional layers -> Detect patterns from edges to complex shapes
- 2 fully connected layers -> Combine features for final classification



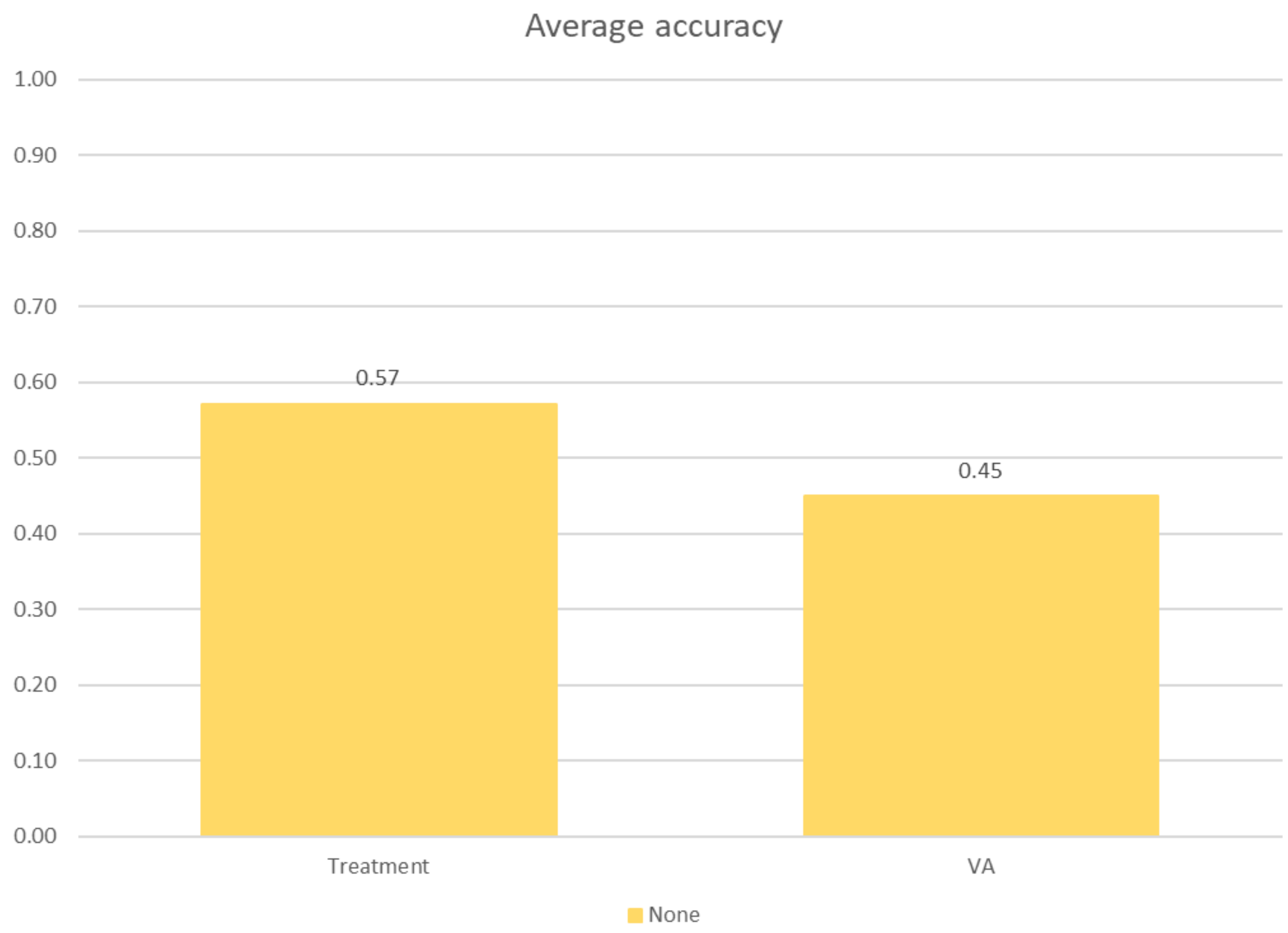
Approach 3 - Transfer learning

Use knowledge from a pretrained model to improve performance on target task



Baseline Performance (No Augmentation)

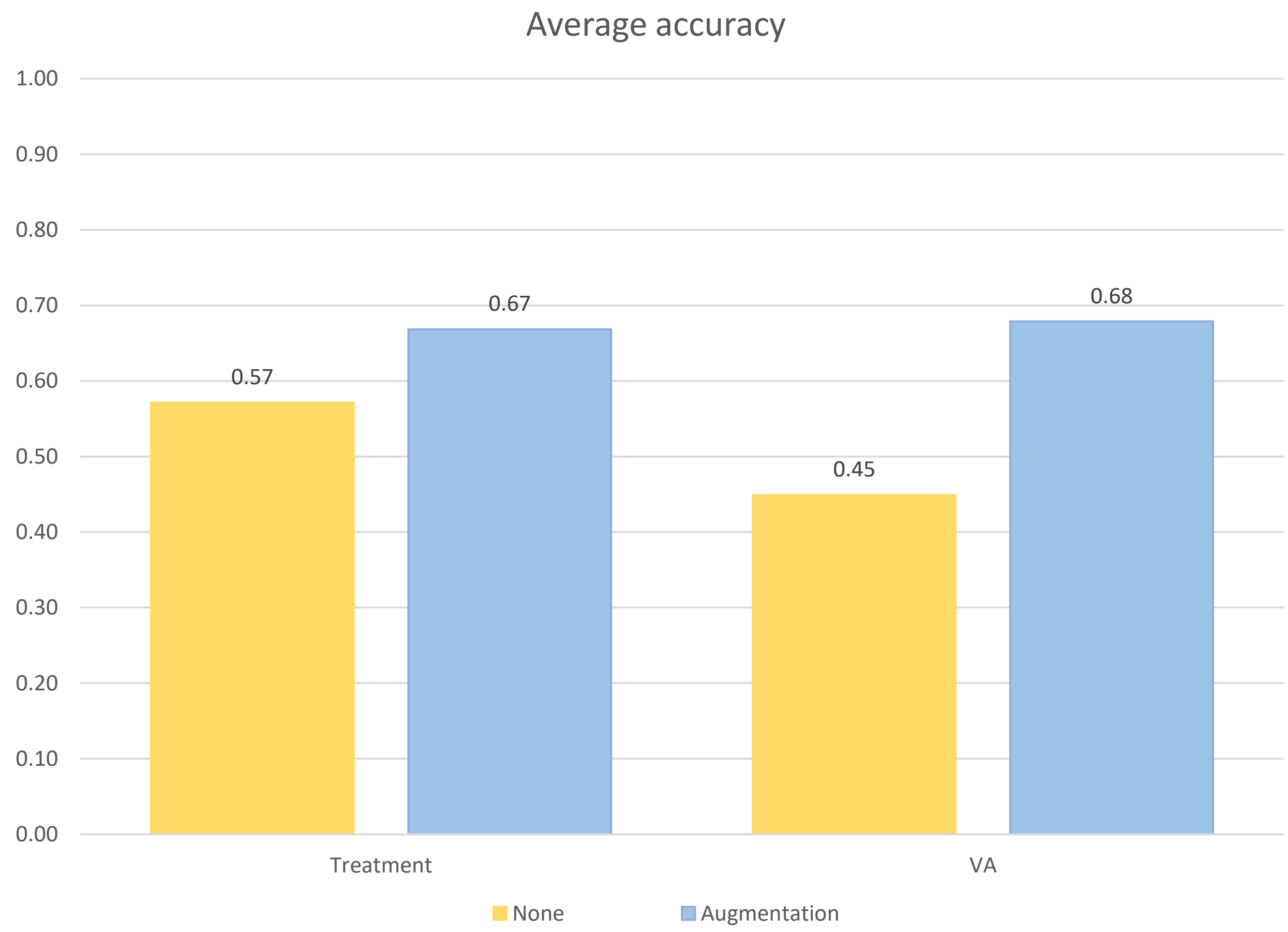
Treatment, VA -> Around 0.5



Improvement 1: Data Augmentation

Treatment: 0.57 -> 0.67

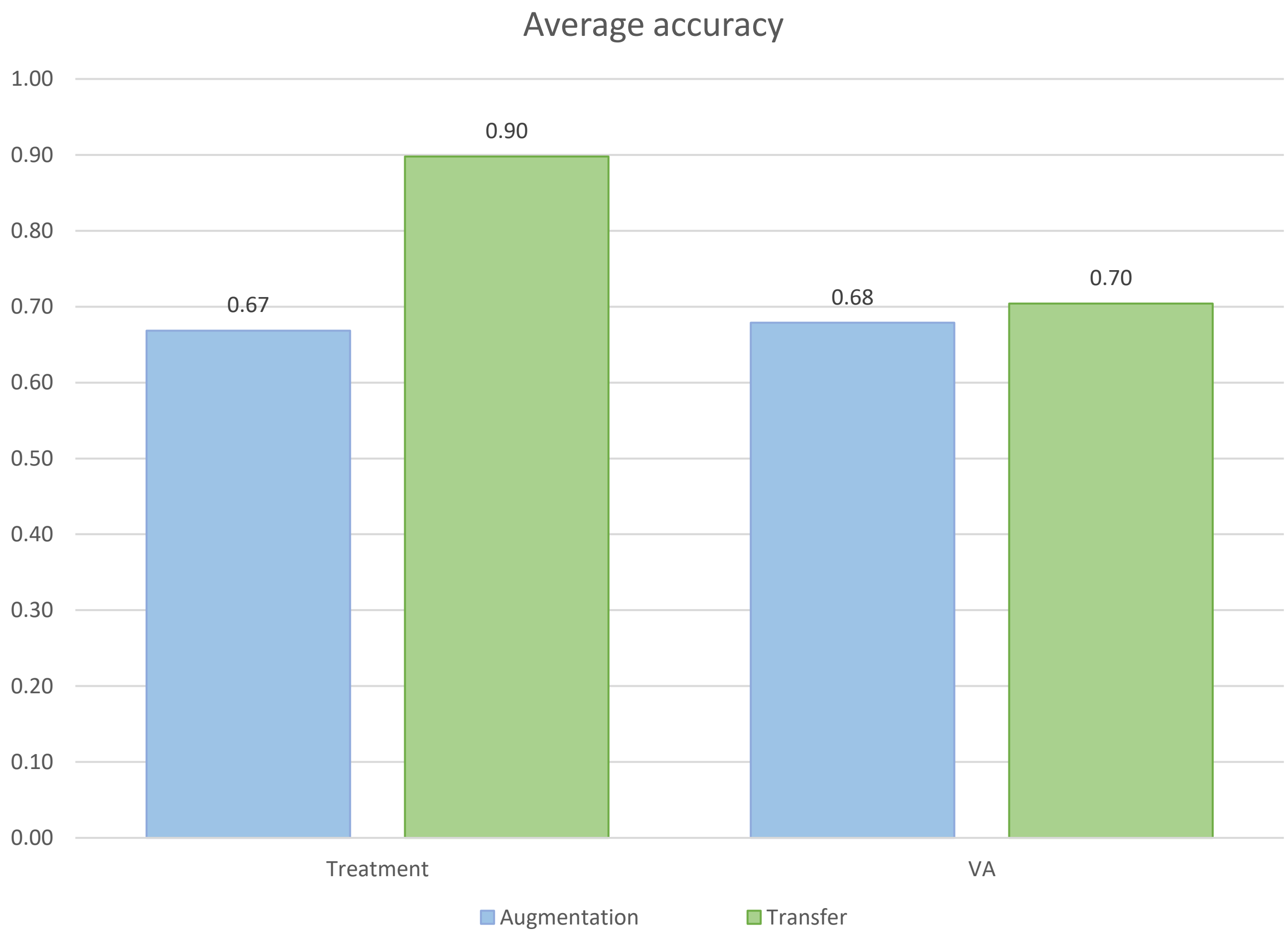
VA: 0.45 -> 0.68



Improvement 2: Transfer Learning

Treatment: 0.67 -> 0.9

VA: 0.68 -> 0.70



Cross-validation

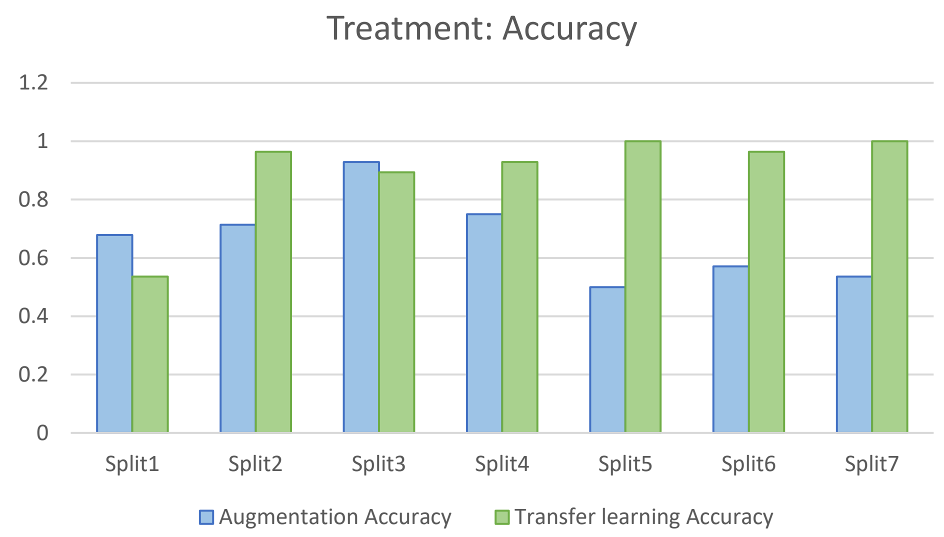
Treatment:

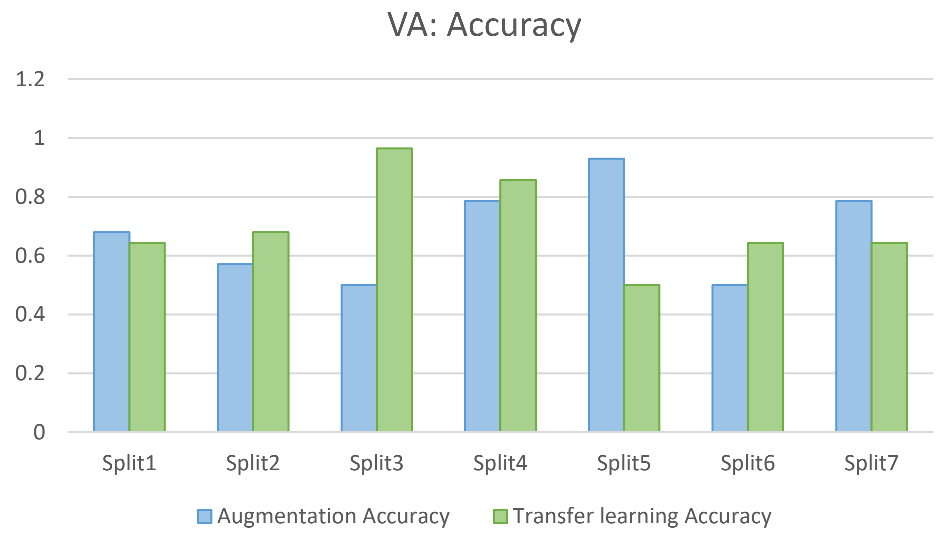
- Augmentation ≈ 0.69 ± 0.15
- Transfer ≈ 0.86 ± 0.20

Visual Acuity (VA):

- Augmentation ≈ 0.68 ± 0.16
- Transfer ≈ 0.71 ± 0.17

- Transfer shows higher mean accuracy but **larger variability across splits**
- Augmentation is slightly more stable





Summary of findings

Without augmentation:

- Treatment > VA

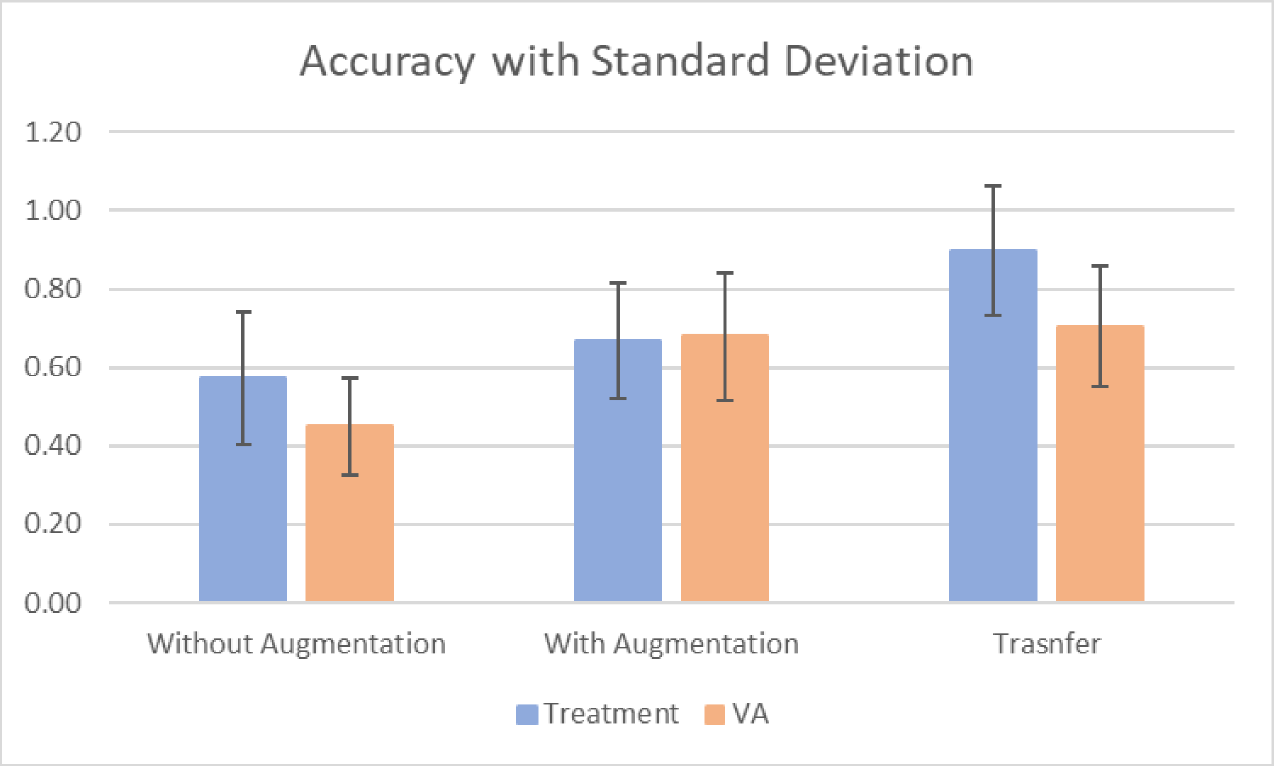
With augmentation:

- Treatment < VA

Transfer learning:

- Treatment > VA

None < Augmentation < Transfer



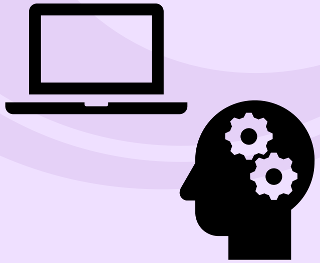
Black box & Explainable AI (XAI)

Clinicians

- Look for **biomarkers** (fluid, PED, SHRM, etc.)
- Use them for diagnosis and treatment planning
- Link biomarkers to prognosis

CNN Model

- Learns patterns directly from OCT images
- Highlights regions contributing most to prediction (e.g. via **Grad-CAM**)
- Ideally aligns with clinical biomarkers



Correlation between Treatment and VA

Very low correlation between treatment and vision. → **0.086585**

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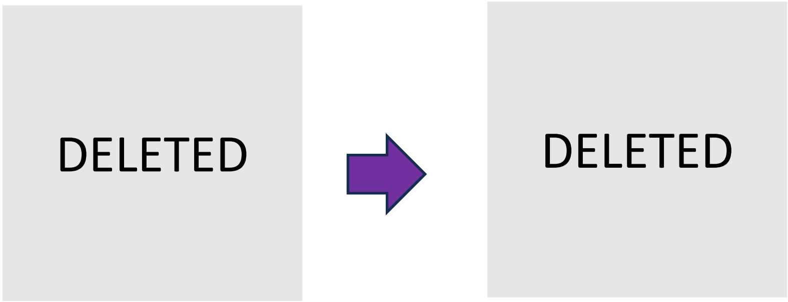
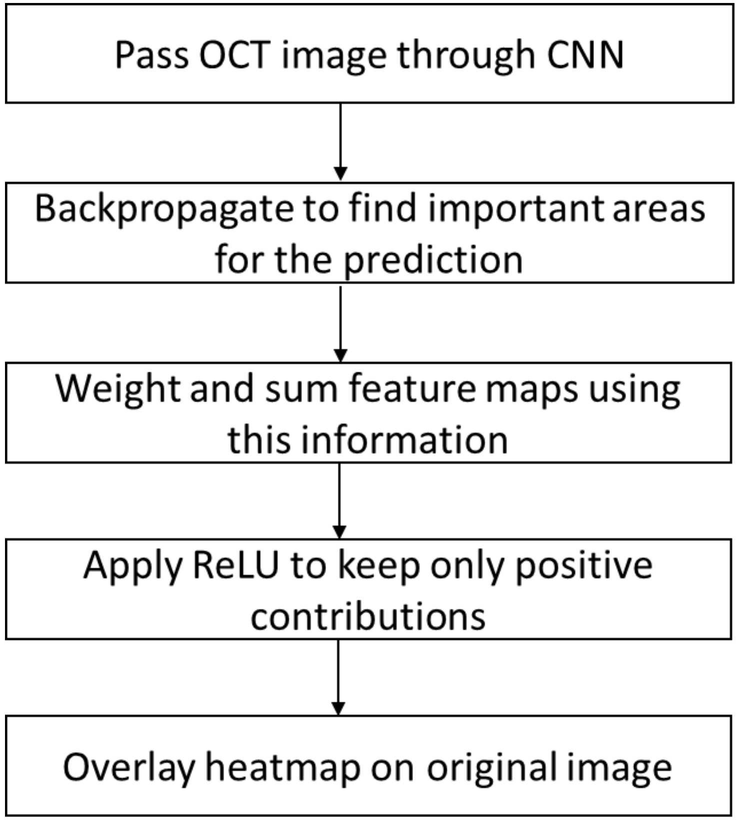
Grad-Cam

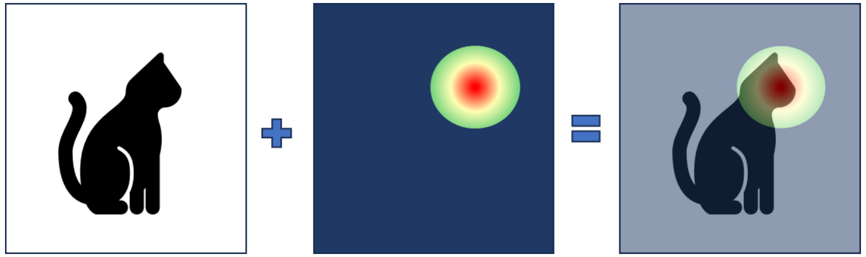
- Highlights regions in an image that influence the CNN's prediction
- Supports clinical validation and interpretability

In This Study

- Applied to each model's predictions (were verified by ophthalmologists)







Result - Grad-Cam

Treatment frequency
Focuses on **localised lesions or specific regions**

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. **Visual acuity**
Focuses on the **overall retinal structure**.

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Model Performance from Clinician Perspective

- Model struggles to detect **intra-retinal and subretinal fluid** consistently
- Performs better at identifying **highly reflective material** in certain cases
- Some false positives/negatives remain, highlighting the need for further refinement

Discussion

- **Augmentation** generally boosts treatment prediction accuracy.
- VA prediction is **less** affected by augmentation, needing tailored strategies.
- **Transfer learning** yields the best accuracy, especially for treatment.
- Accuracies vary per **split**, so task-specific tuning is essential.

Summary

Findings

- CNN with augmentation is effective on small datasets
- Transfer learning achieves higher accuracy but risks of overfitting
- Grad-CAM improves interpretability, but clinical alignment is limited

Future Work

- Larger datasets to improve stability and reduce overfitting
- Multi-class prediction for Treatment; regression for VA
- Stronger validation strategies