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

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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

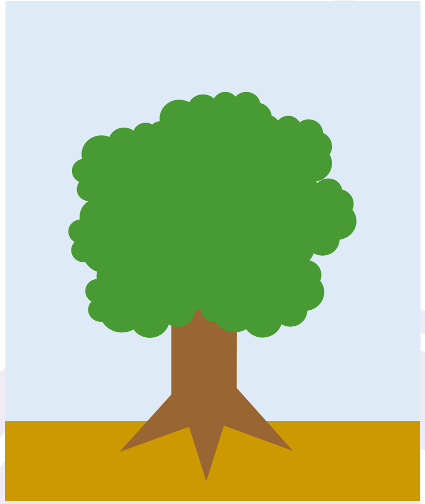
A Leading Cause of Vision Loss

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

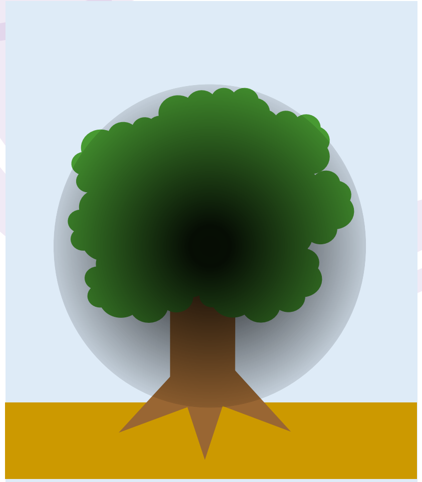
Rising Cases with an Ageing Population

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

Normal Vision



Vision in nAMD



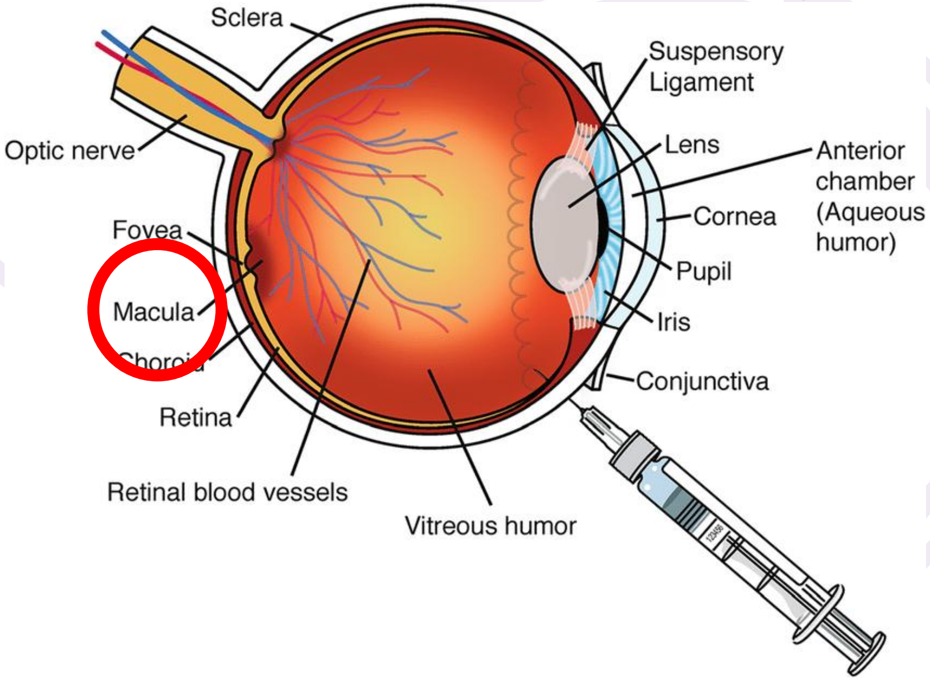
AMD types

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



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

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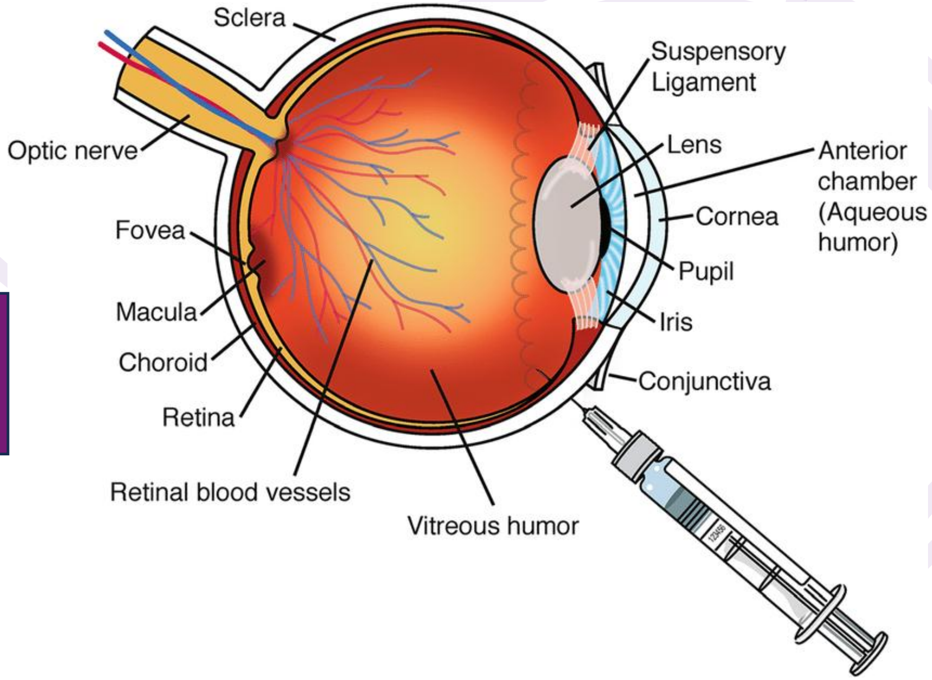
OCT Images



“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

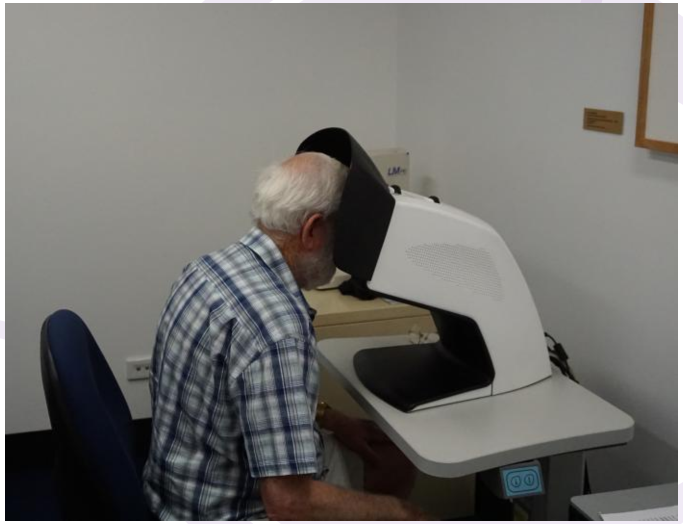


Image credit: spelio, Flickr (CC BY 2.0)
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What does an OCT scan look like?

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

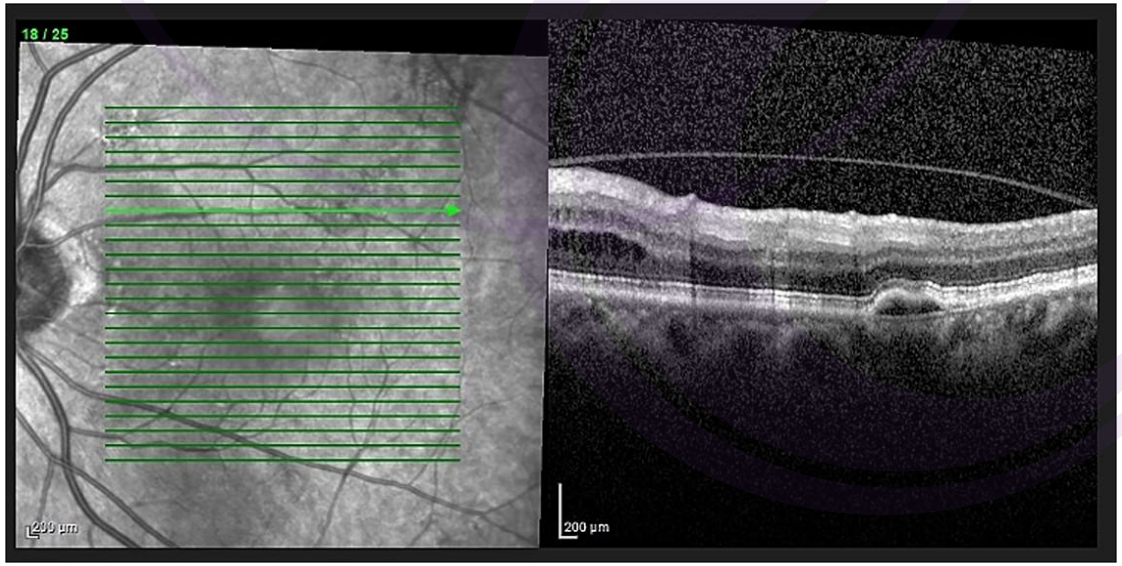

Figure2. “Figure 3 OCT of left eye – showing IRF... | Oxford Academic,” n.d

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)?

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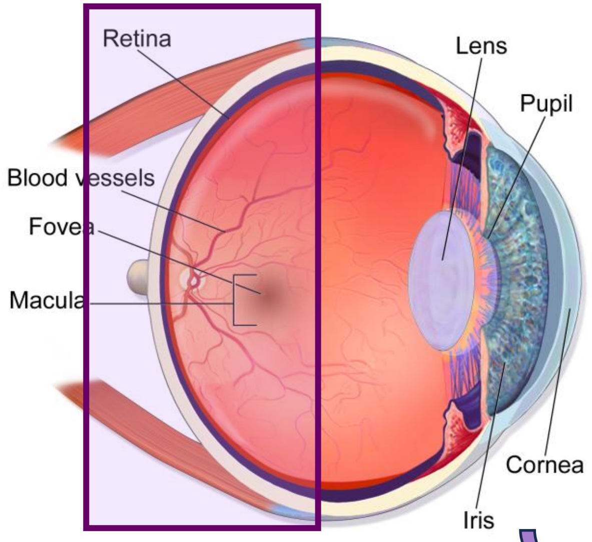
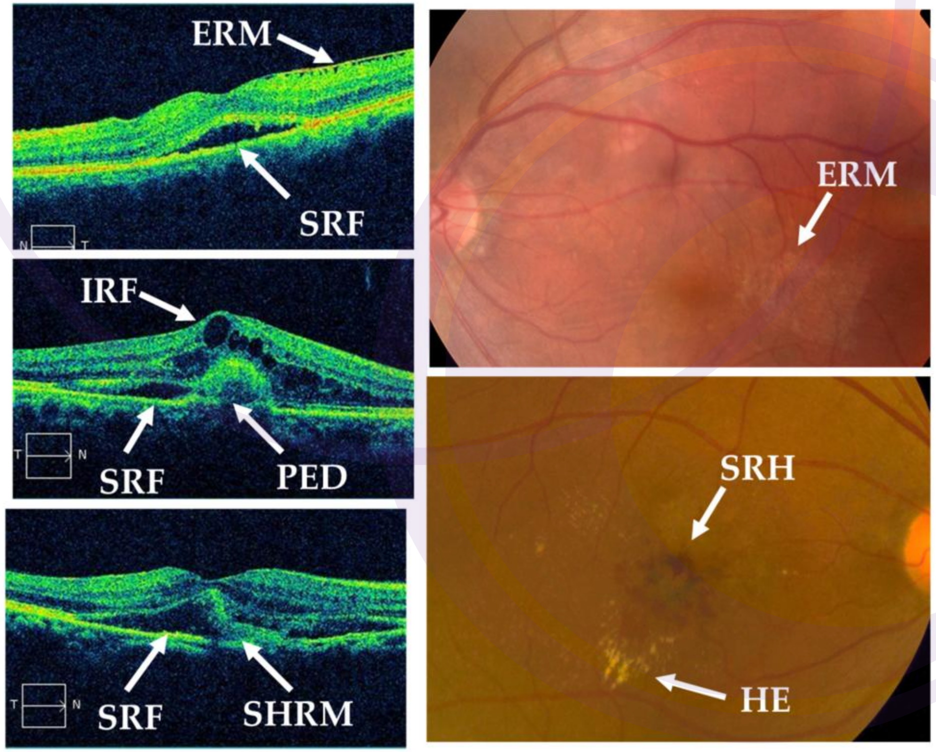
How to predict?

Key Biomarkers - Features linked to disease

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



Eye Anatomy

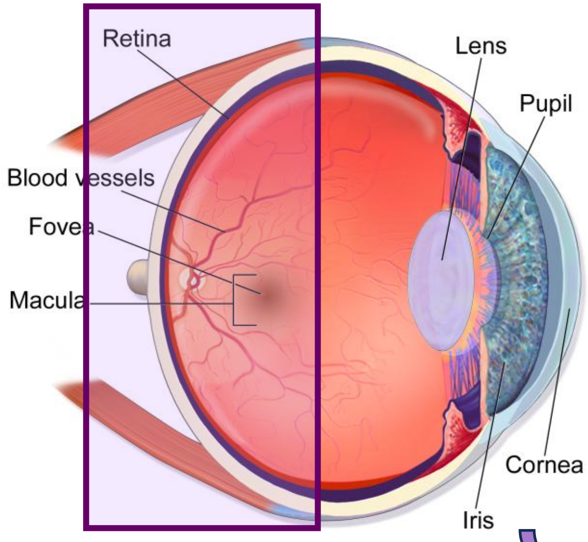


"jcm-13-06244-g001.png," n.d.

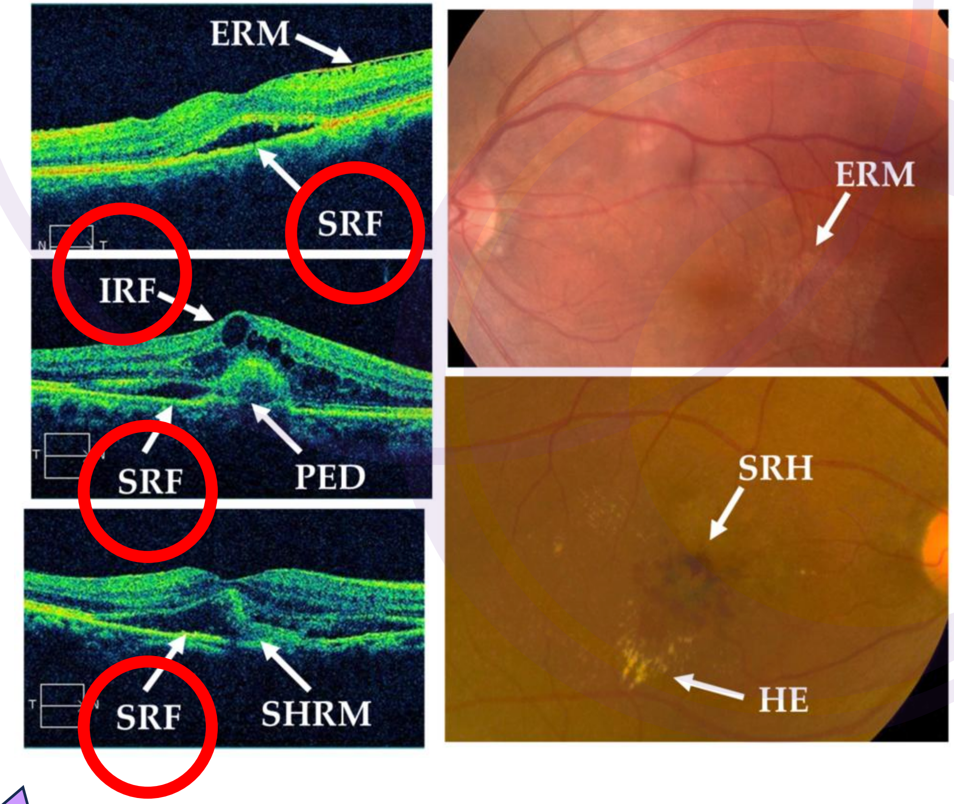
Key Biomarkers

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

Fluid - low signals



Eye Anatomy

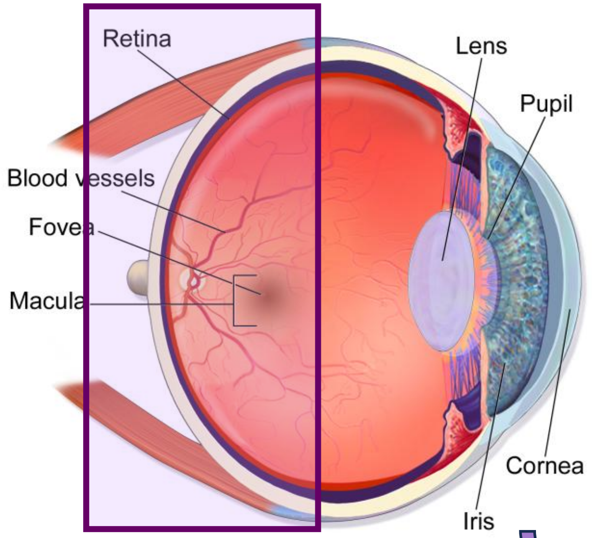


"jcm-13-06244-g001.png," n.d.

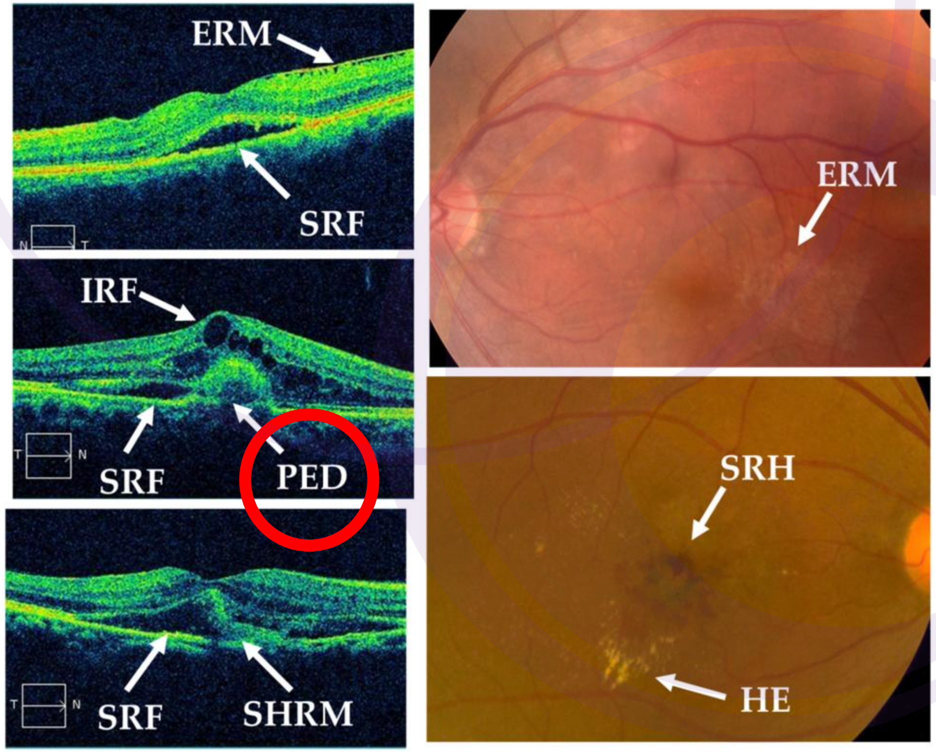
1-2. Key Biomarkers

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



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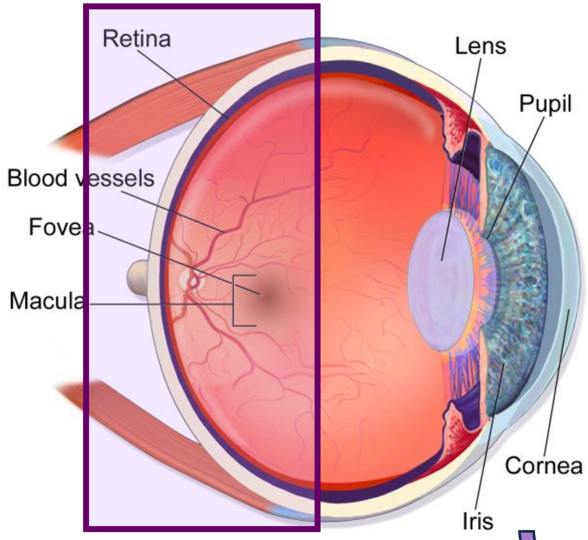
Eye Anatomy. Image by Blausen.com staff, 2014, used under CC BY 3.0 License. Available at: https://commons.wikimedia.org/wiki/File:Blausen_0389_EyeAnatomy_02.png

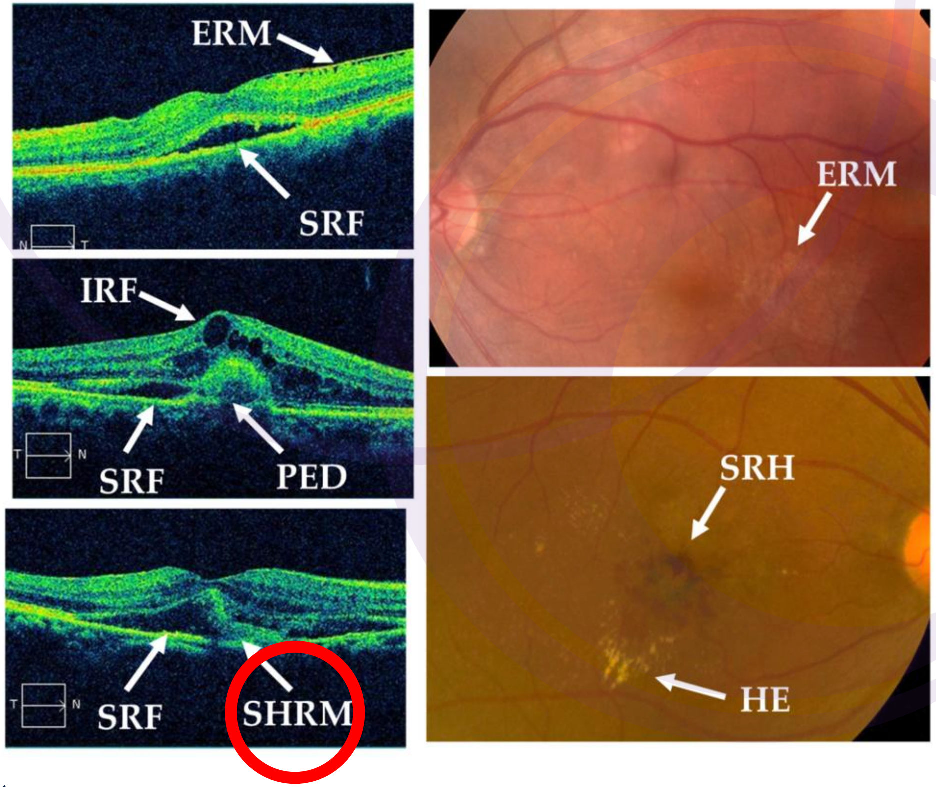
1-2. Key Biomarkers

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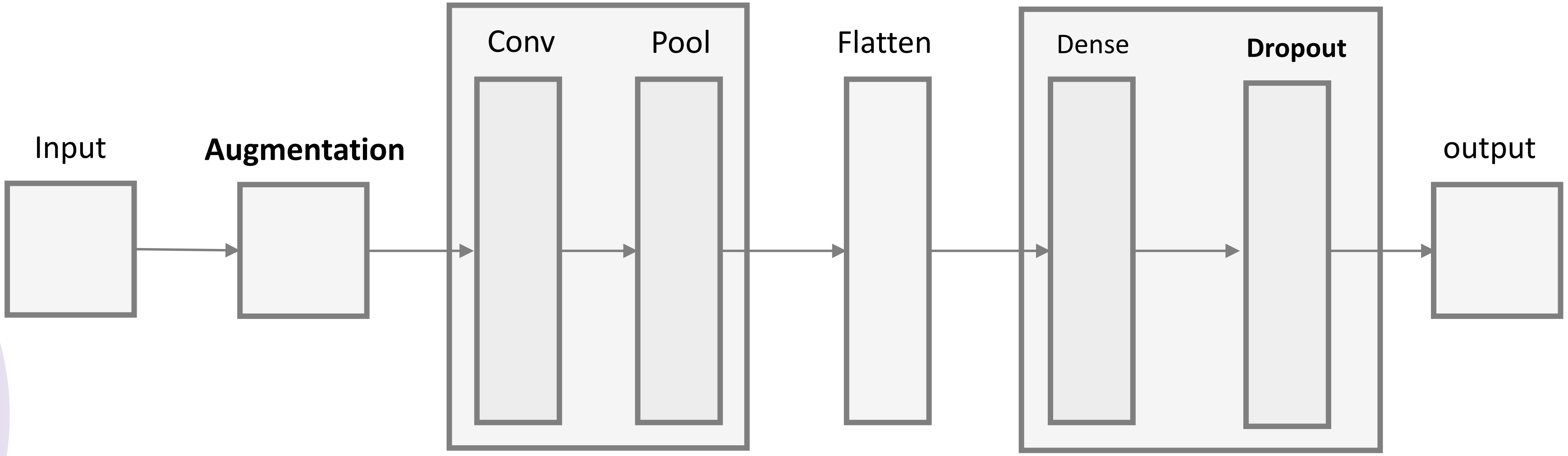
Eye Anatomy. Image by Blausen.com staff, 2014, used under CC BY 3.0 License. Available at: https://commons.wikimedia.org/wiki/File:Blausen_0389_EyeAnatomy_02.png

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

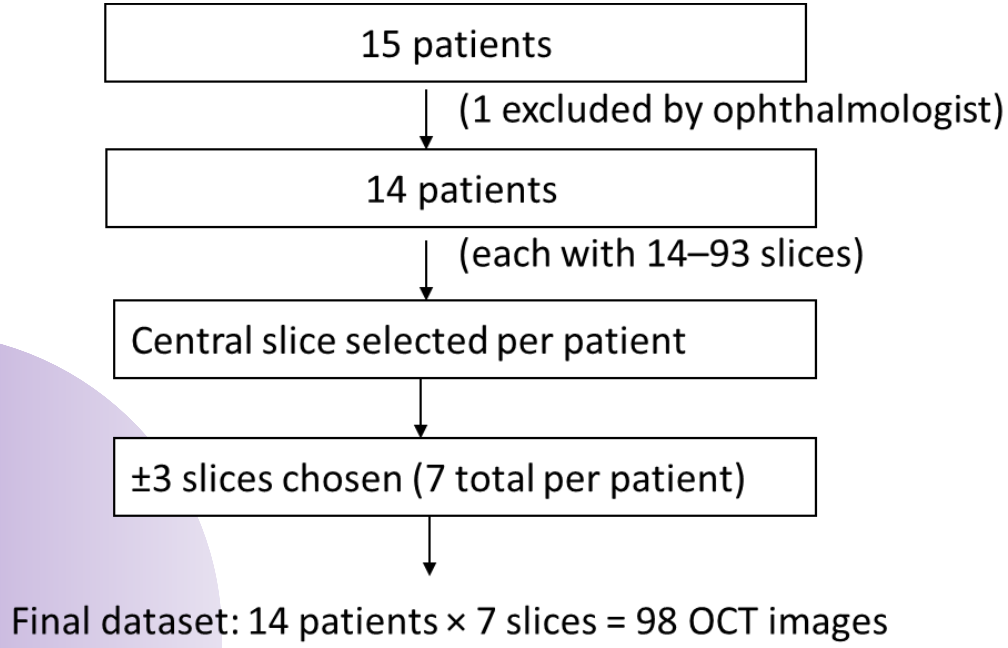
- OCT scans from the Heidelberg Spectralis system

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

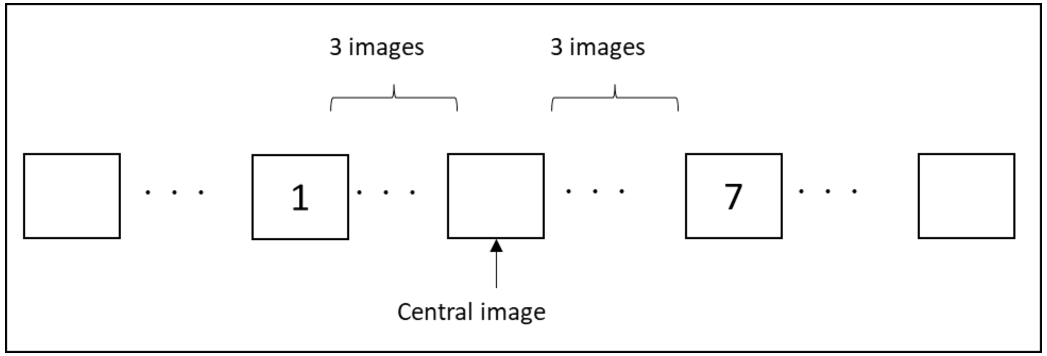
→Multi-site data ensures diversity in imaging and clinical cases

Dataset & Preprocessing

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

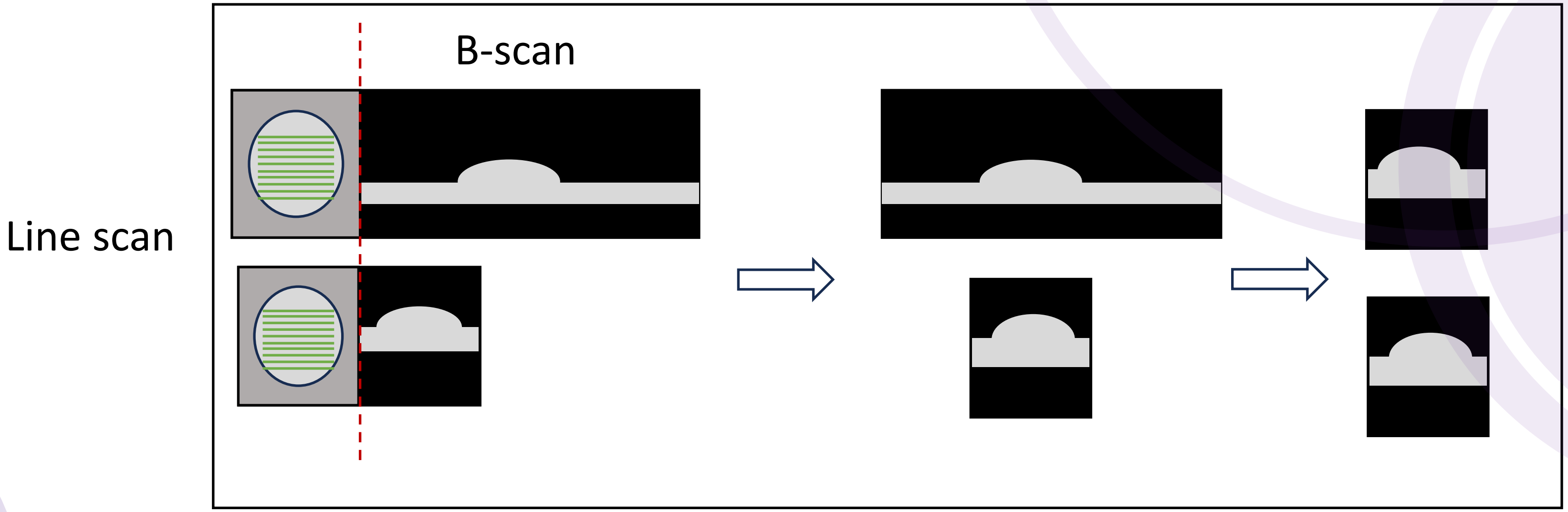


2. Selected **7** important slices per patient



Dataset & Preprocessing

3. Cropped and resized images to **450** × **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)

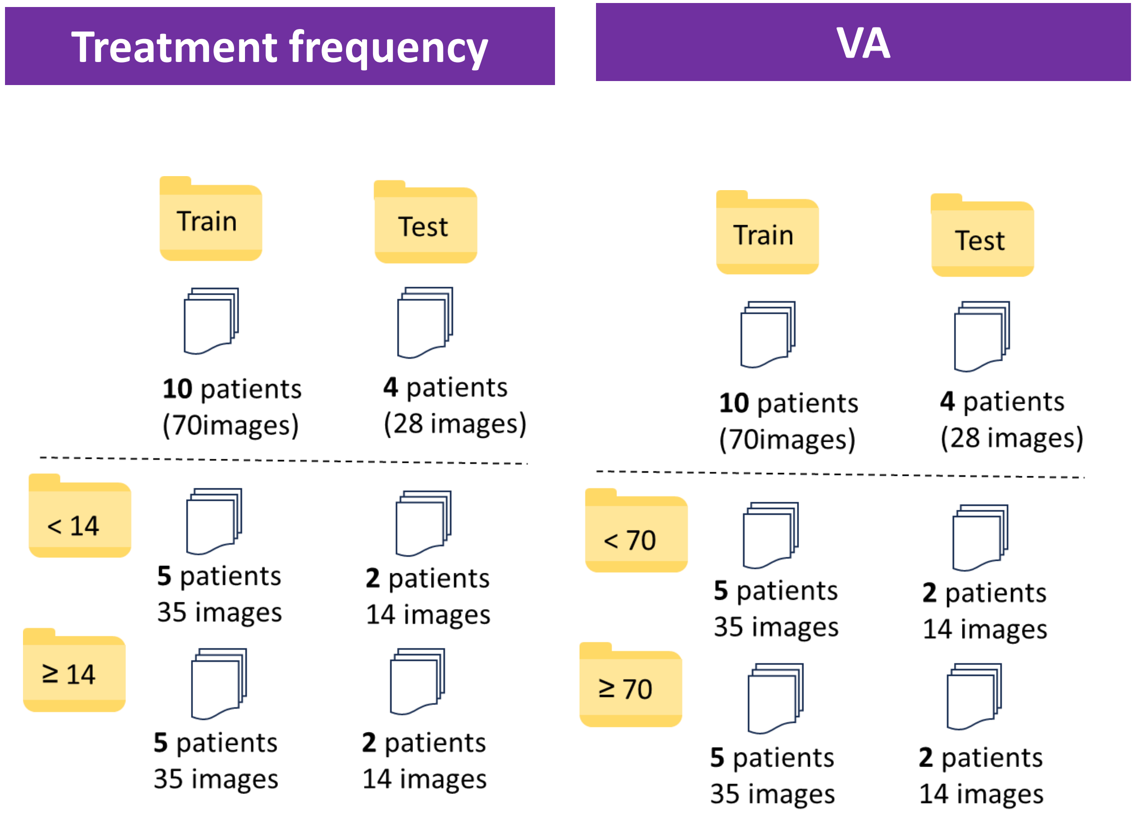
Low

High

Two groups each:

- Treatment frequency: < **14** or ≥ **14**
- Visual acuity (words) : < **70** or ≥ **70**

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



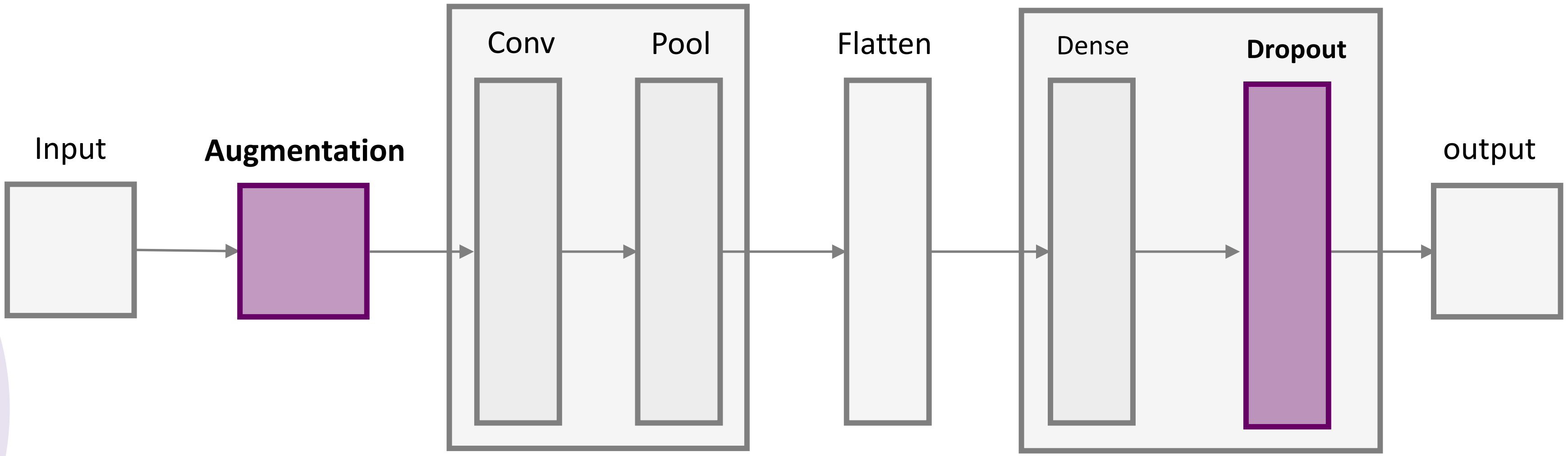
Models

- 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

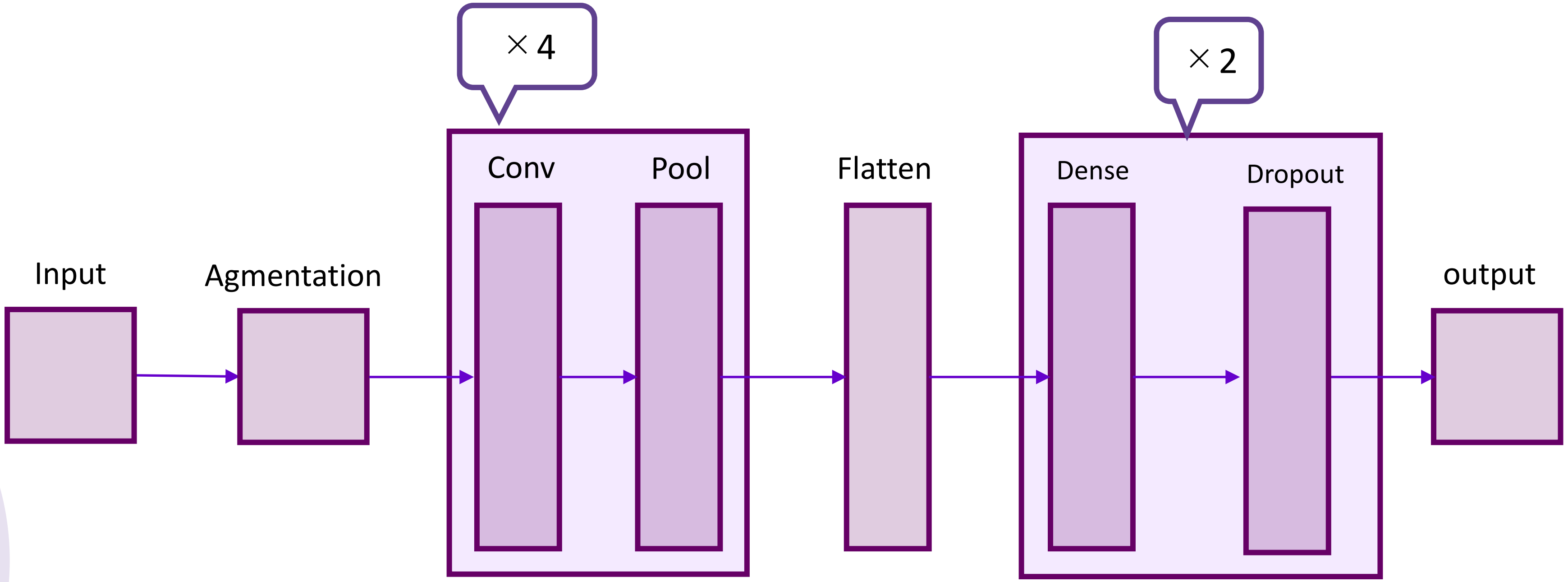
Regularisation:
batch normalisation, dropout layers, early stopping — prevents overfitting



Baseline CNN Model

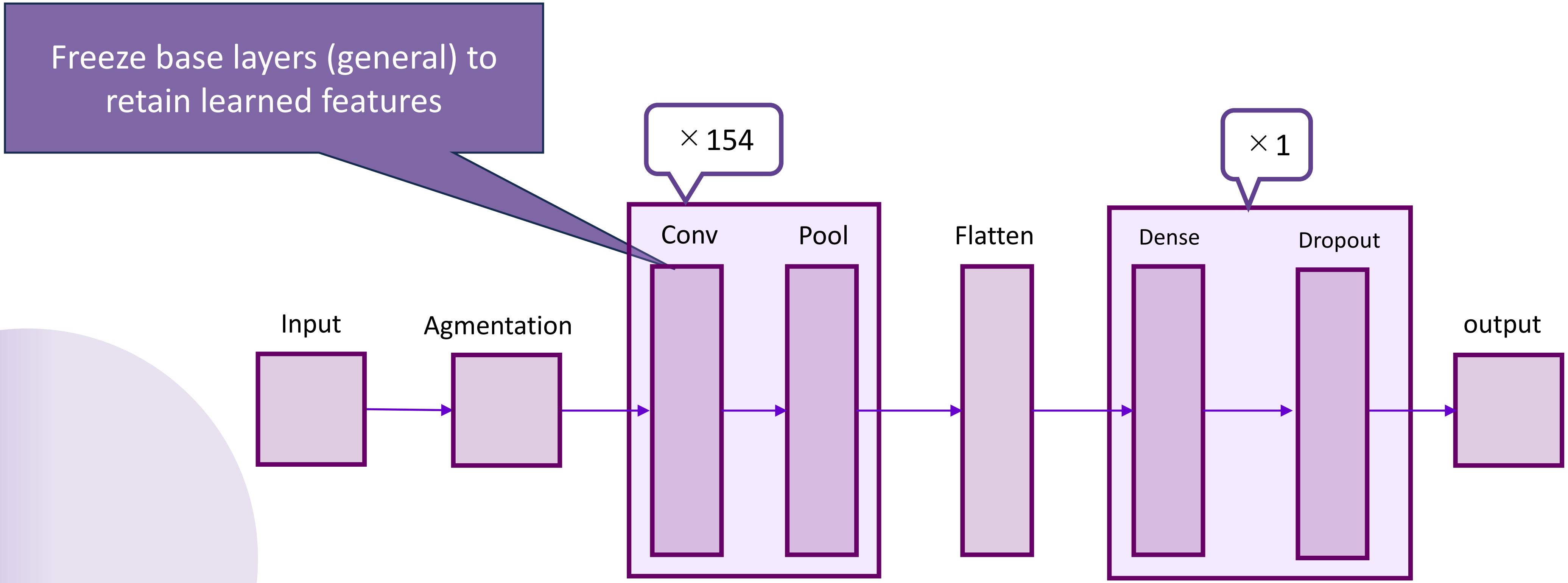
Model Architecture

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



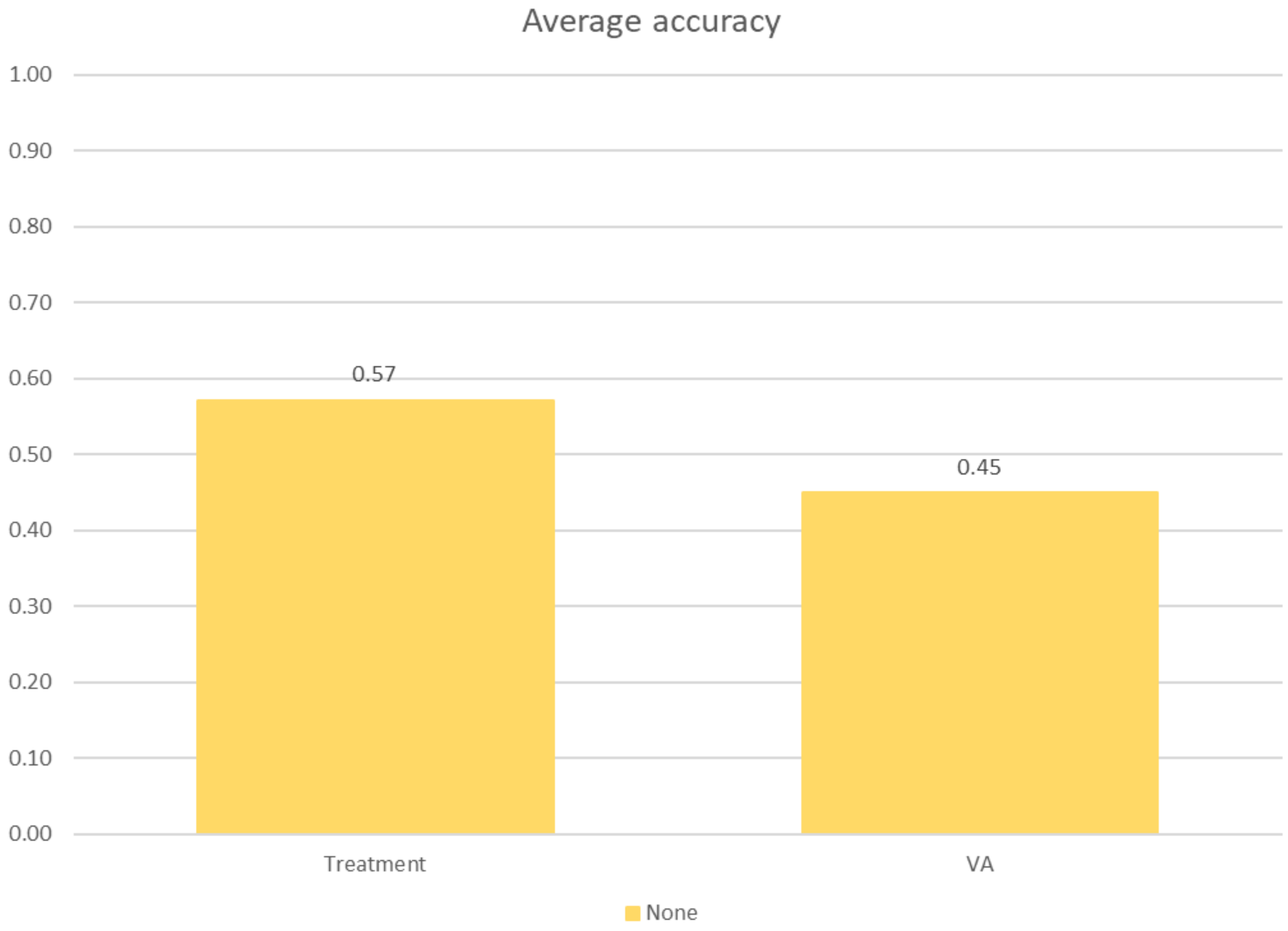
Approach 3 - Transfer learning

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



Baseline Performance (No Augmentation)

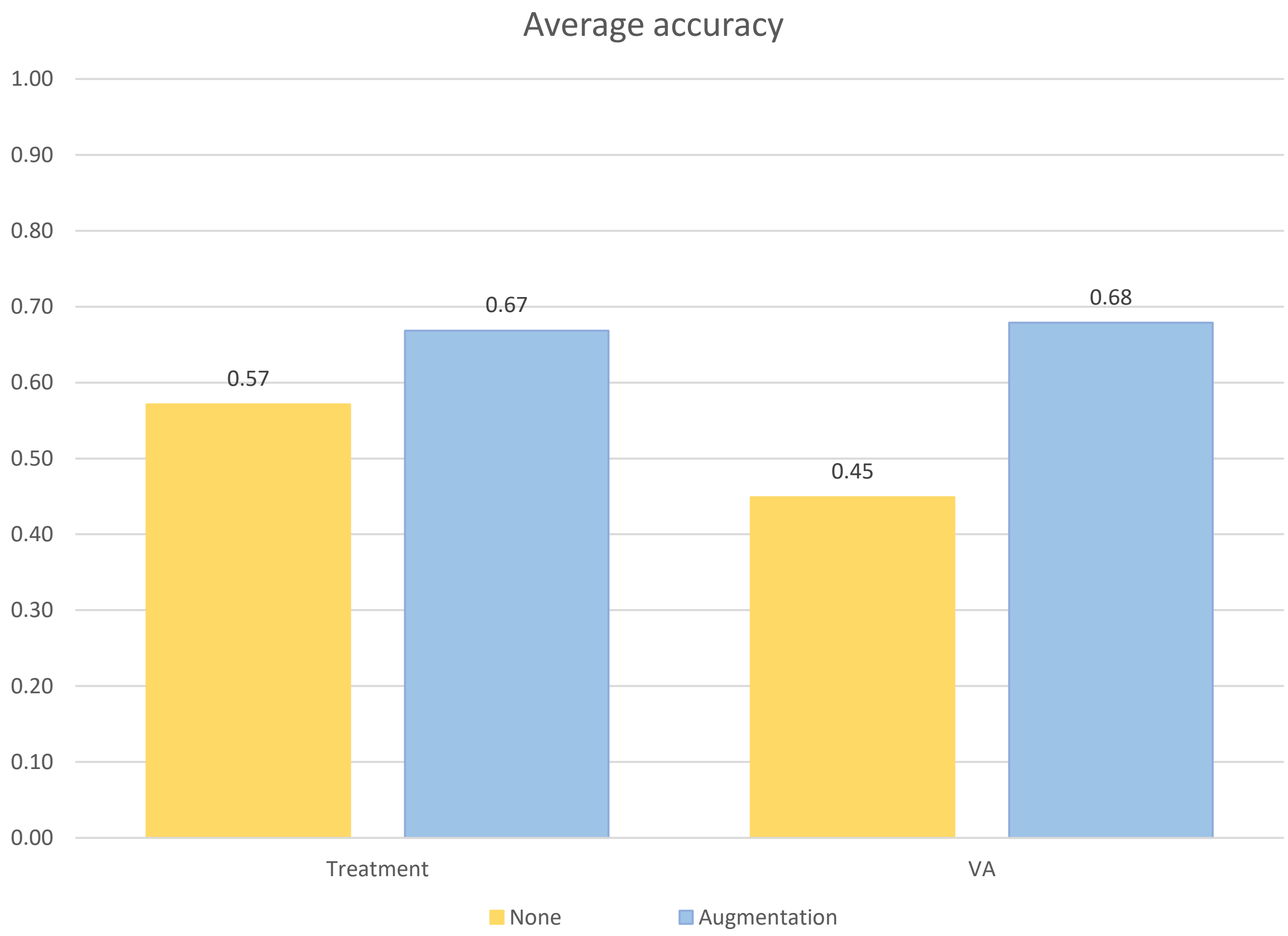
Treatment, VA -> Around 0.5



Improvement 1: Data Augmentation

Treatment: 0.57 -> 0.67

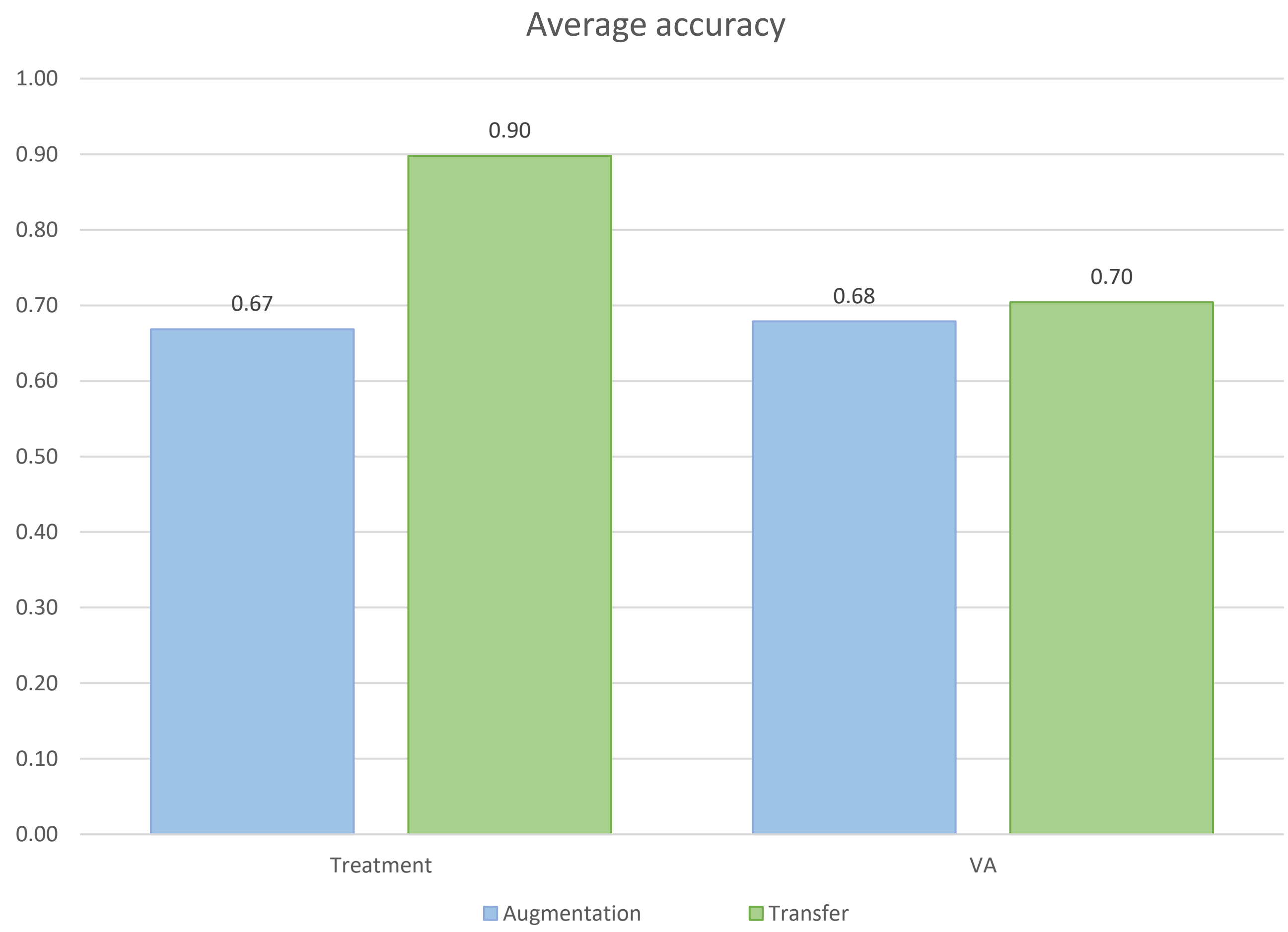
VA: 0.45 -> 0.68



Improvement 2: Transfer Learning

Treatment: 0.67 -> 0.9

VA: 0.68 -> 0.70



Cross-validation

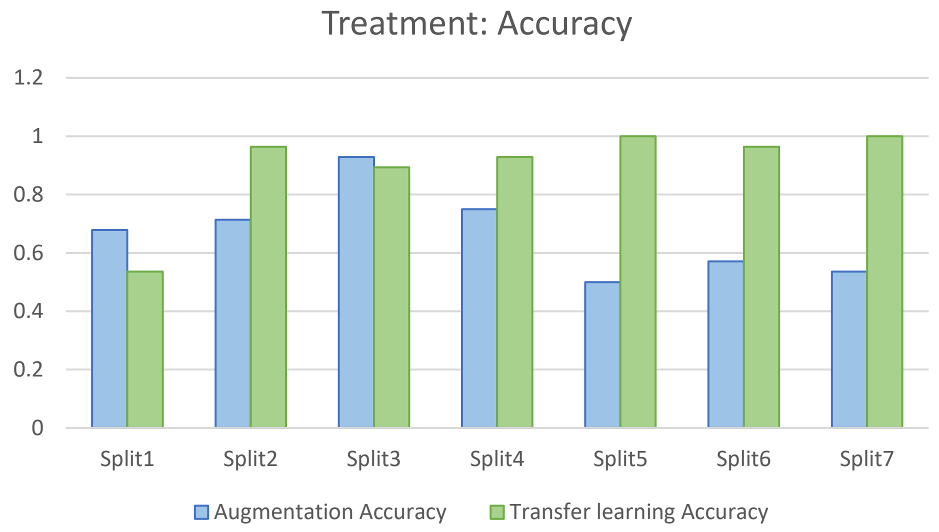
Treatment:

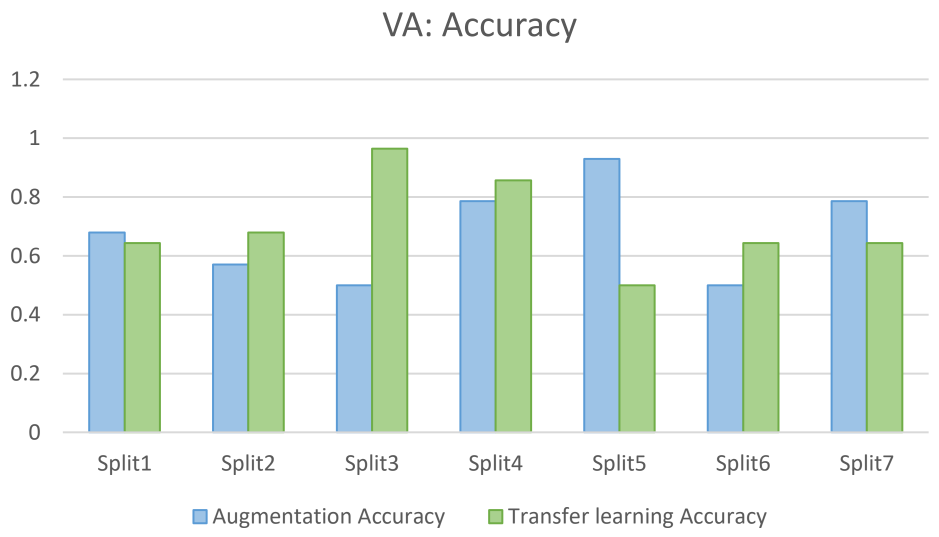
- Augmentation ≈ 0.69 ± 0.15
- Transfer ≈ 0.86 ± 0.20

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

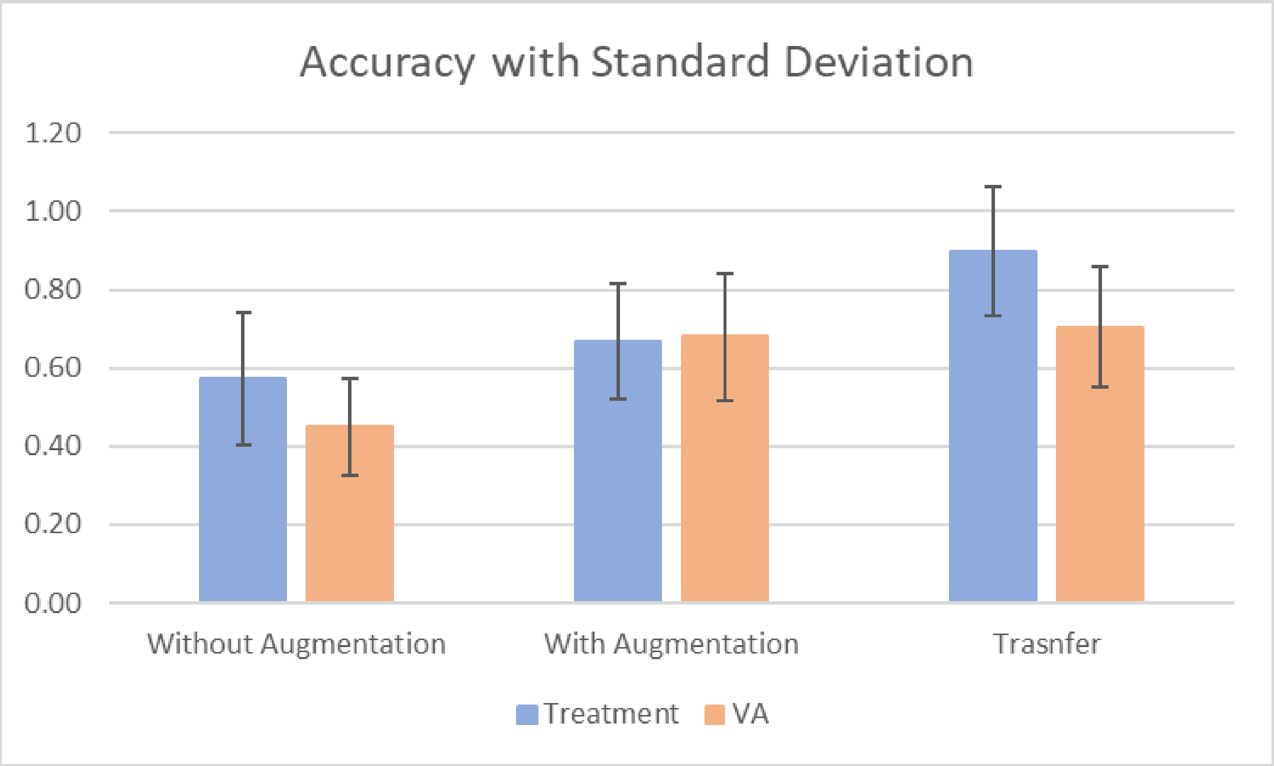
With augmentation:

- Treatment < VA

Transfer learning:

- Treatment > VA

None < Augmentation < Transfer



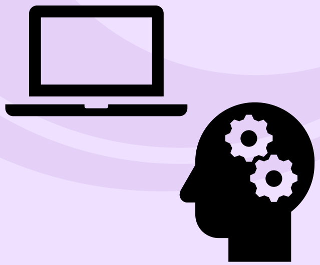
Black box & Explainable AI (XAI)

Clinicians

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

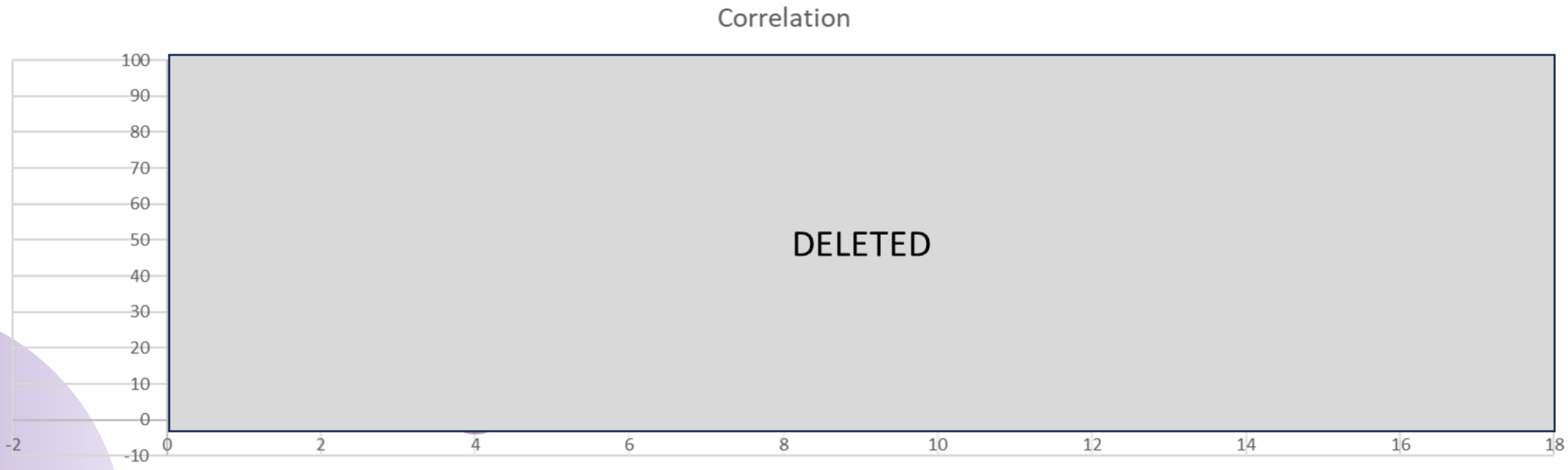
CNN Model

- 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**



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)

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Pass OCT image through CNN

↓

Backpropagate to find important areas for the prediction

↓

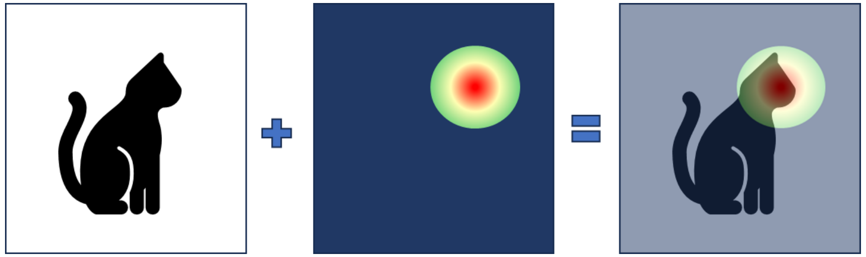
Weight and sum feature maps using this information

↓

Apply ReLU to keep only positive contributions

↓

Overlay heatmap on original image



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

CNNs layers

Layer	Feature Type	Description	Biomarkers
Shallow layers	Edges	Detects boundaries, contours, and transitions in light and dark areas, helping to identify retinal layers in OCT images.	
Shallow layers	Textures	Captures surface patterns and fine structures in the image, such as the textures of the retinal pigment epithelium and neuroretina.	
Shallow layers	Lines and Shapes	Detects straight lines, curves, and simple geometric shapes, useful for detecting retinal layers and abnormalities.	
Deep layers	Complex Patterns	Detects complex shapes and structures, such as retinal layers and abnormalities (e.g., IRF, SRF, PED), combining edges and textures from shallow layers.	IRF, SRF, PED
Deep layers	Abstract Features	Captures subtle changes, such as fluid accumulation (e.g., SRF, PED), that are essential for disease detection in OCT images.	SRF, PED
Very deep layers	Higher-Level Structures	Combines multiple layers to understand larger structures like full retinal layers or lesion sites, helping to identify lesions and abnormalities.	IRF, SRF, PED