Classification of macular degenerative pathologies from OCT images with speckle noise

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BME 541L: Machine Learning and Imaging

MEng in Photonics and Optical Sciences

Duke

Presentation Agenda

- Background and Motivation
- Data Capture: Optical Coherence Tomography
- Speckle Noise
- Machine Learning Pipeline
    - Dataset
    - Preprocessing
    - Cleaning up Speckle Noise
    - Classification
- Results
- Conclusions

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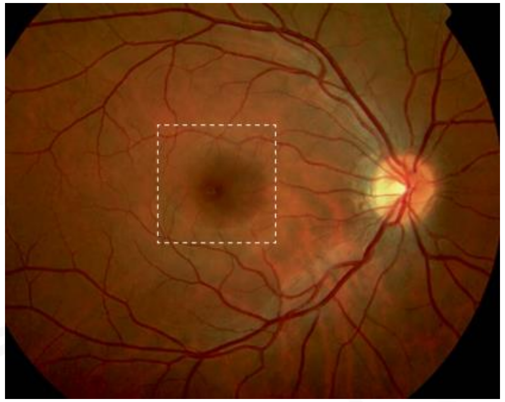
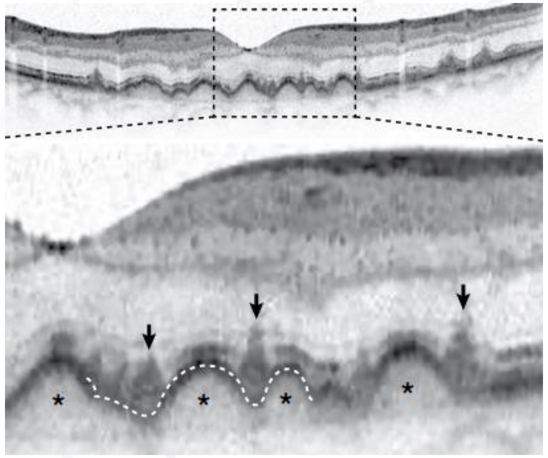
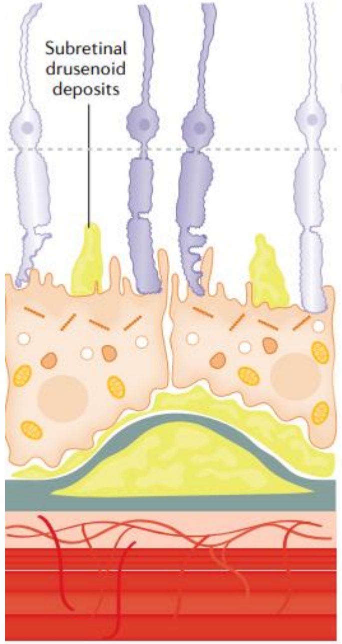
Background and Motivation



- Age-related macular degeneration (AMD) is the leading cause of legal blindness in individuals > 55 years old
- AMD accounts for 6 – 9% of legal blindness globally
- Several different pathologies associated with AMD:
  - Choroidal neovascularization (CNV)
  - Drusen
  - Diabetic Macular Edema (DME)
- Each pathology has its own symptoms, progression timelines, treatments, etc.
- Need for rapid retinal imaging and classification techniques for early detection and vision loss prevention





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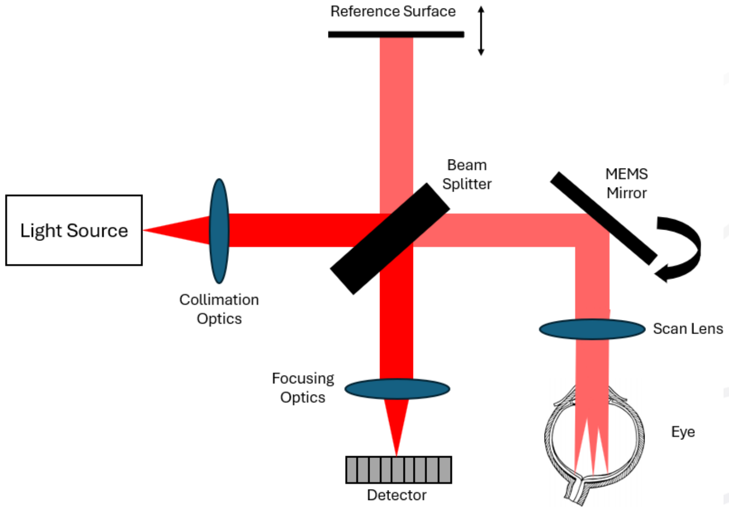
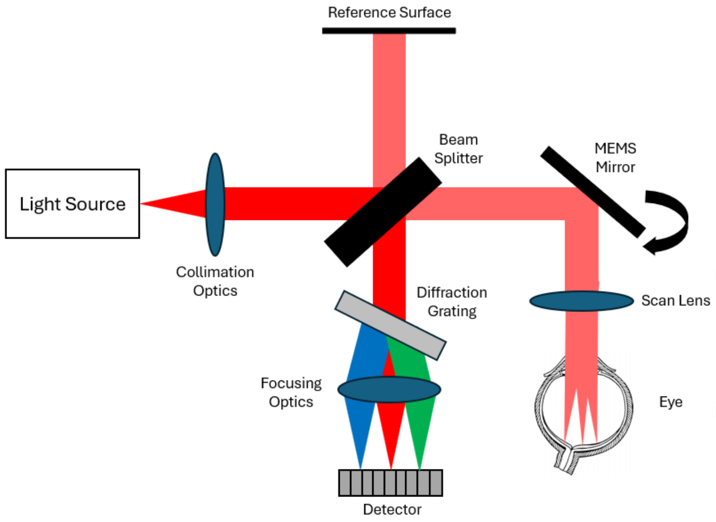
Optical Coherence Tomography (OCT)

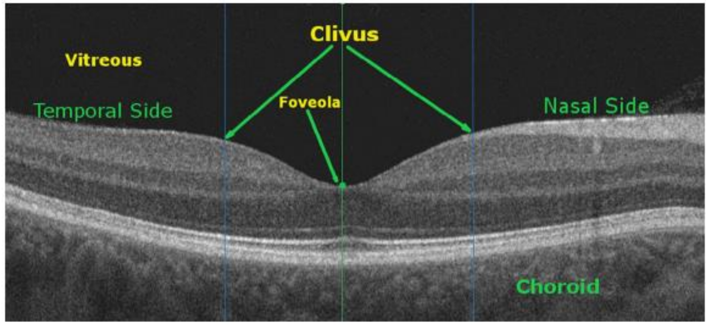
- Rapid, noninvasive, single-cell resolution medical imaging technique
- Clinical gold standard in retinal imaging
- Interferometric imaging using backscattered light from biological samples
- Dependent on coherence properties of light source



Time-Domain System



Fourier-Domain System



B-Scan Image

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Speckle Noise

<u>Coherence</u>

- Fixed phase relationship between electromagnetic field values at:
  - (1) different locations (Spatial Coherence)

    OR
  - (2) different times (Temporal Coherence)
- Can be modified by bandwidth of source or spatial filtering of beam
- Axial resolution of OCT imaging dependent on coherence length of source:

$$l_c \approx 0.44 \frac{\lambda_c^2}{\Delta\lambda}$$

Lower coherence = higher resolution !!

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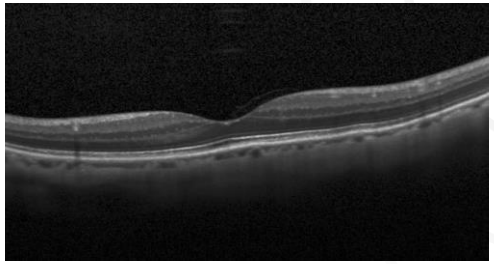
<u>Speckle Noise</u>

- Interference between different parts of an object due to scattering
- Manifests as random fluctuation in intensity (noise)
- Degrades overall image quality
- Can be quantified using speckle contrast (C_s):

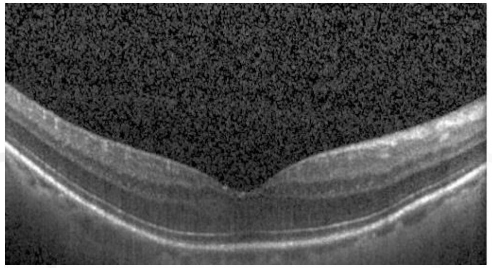
$$C_s = \frac{\sigma_n}{\langle I \rangle}$$

σ_n: standard deviation of image intensity

$\langle I \rangle$: mean image intensity

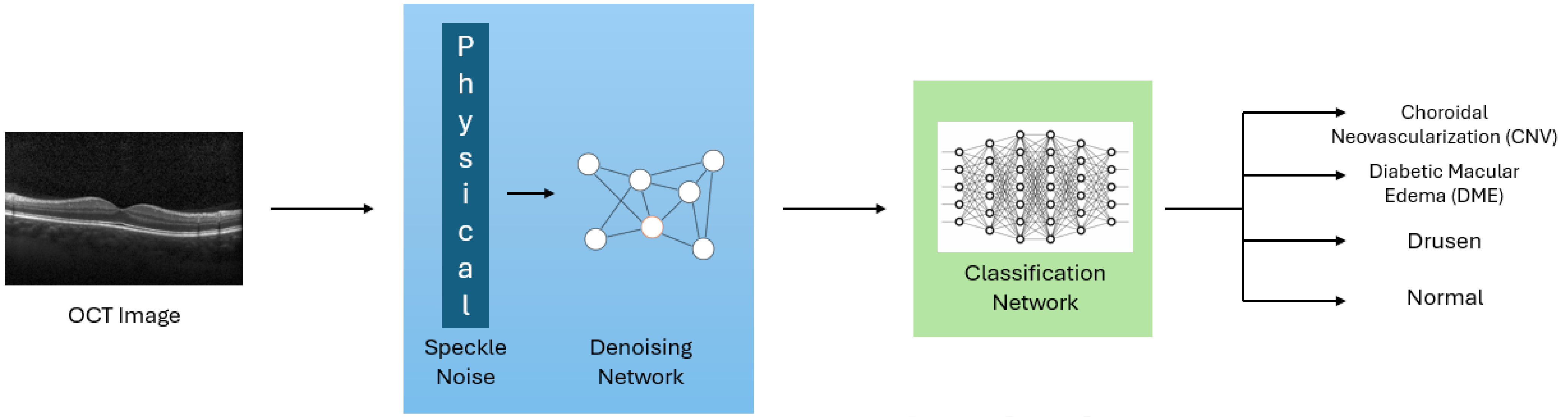


Low Speckle Noise



High Speckle Noise

Machine Learning Pipeline



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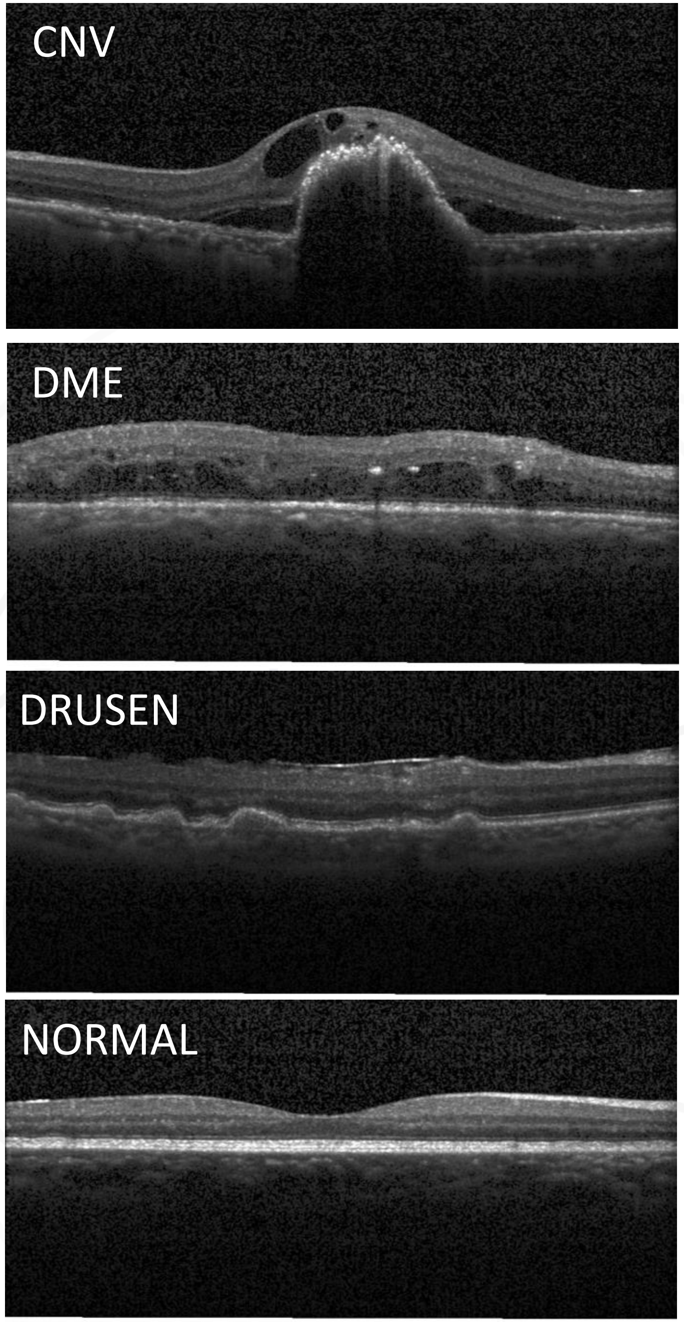
Dataset

- Data taken from “Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images”

  Daniel Kermany et al., University of California San Diego, Guangzhou Women and Children’s Medical Center
- OCT dataset:
  - 109,309 total images
    - 1,000 test images
    - 108,309 training images
  - Broken up into four main categories, based on AMD pathology
    - 37,455 choroidal neovascularization images (CNV)
    - 11,598 diabetic macular edema images (DME)
    - 8,866 drusen images (DRUSEN)
    - 51,390 normal images (NORMAL)
  - Varying image sizes, orientations, and speckle noise



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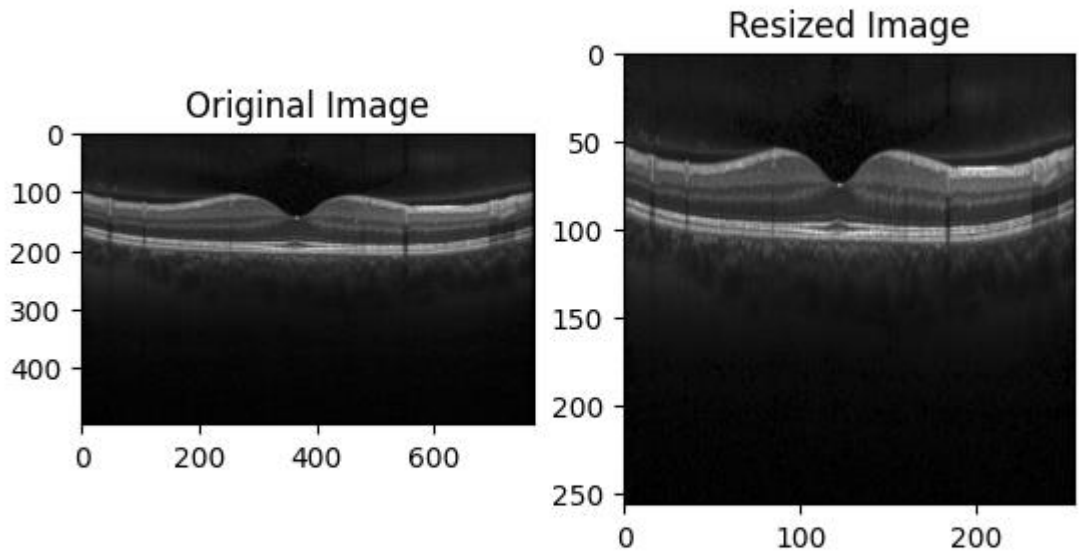
Preprocessing

1. Resizing the dataset:
    - Need images to all have same dimensions for CNN
    - All images resized to be 256 x 256 pixels
    - Aspect ratio threshold set at 1.5:1

    - New Dataset:
        - Total: 42,345 Images
            - Train: 41,345 images
            - Test: 1,000 images

            - CNV: 9,494 images
            - DME: 10,144 images
            - DRUSEN: 5,371 images
            - NORMAL: 16,336 images



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Preprocessing

2. Adding speckle noise:
   - Speckle noise simulated using random phasors:

$$phasor = Ae^{i\phi}$$

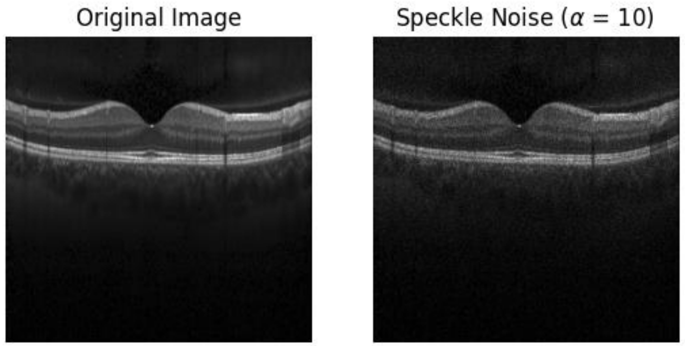
     - Amplitude (A) had a constant value
     - Phase (ϕ) had a unform distribution from $-\pi$ to π
   - A sum of N phasors is added to each pixel to produce the speckle noise in your image

$$Speckled\ Pic = \ \alpha\sqrt{Original\ Pic} + phasorSum$$

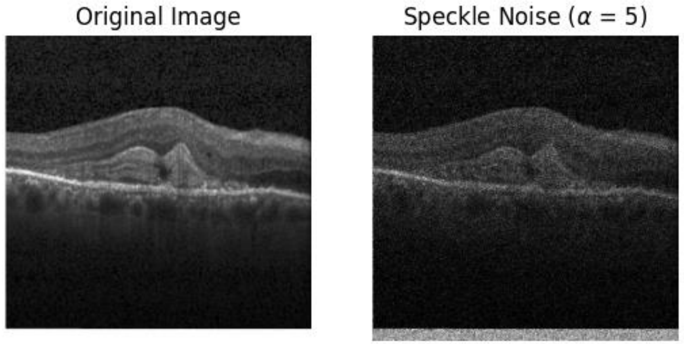
     - α: pre-factor (can be set to any value)

Smaller α = more speckle noise

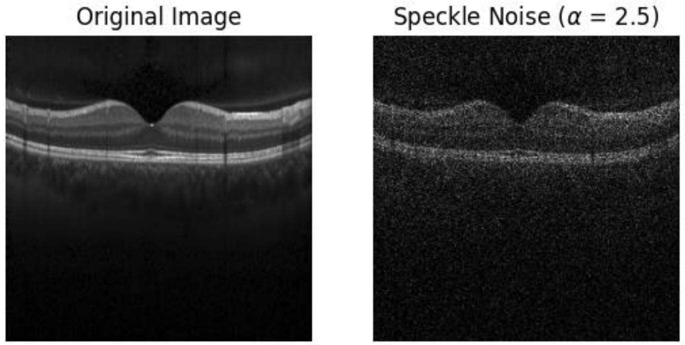
Low Speckle Noise (α = 10):



Medium Speckle Noise (α = 5):

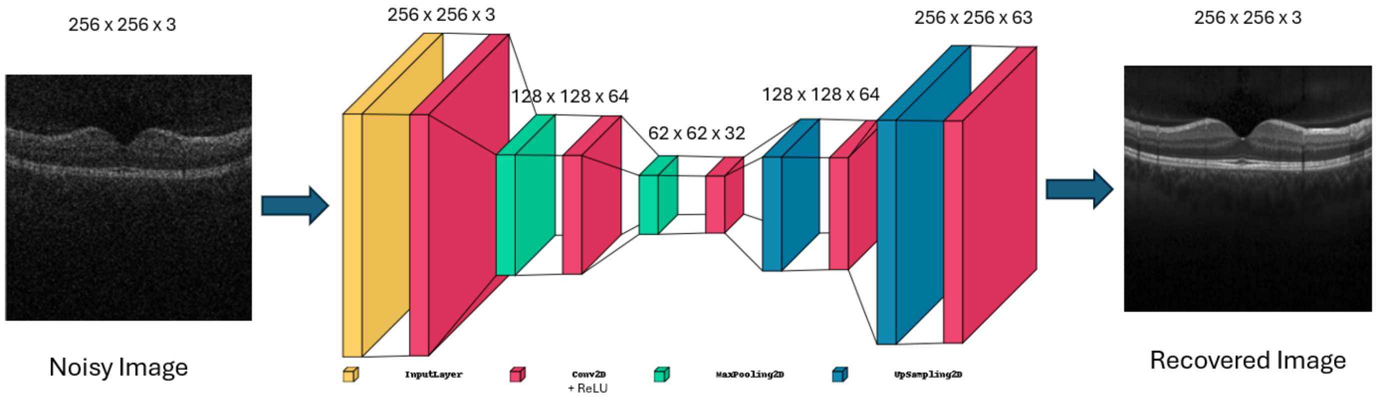


High Speckle Noise (α = 2.5):



Cleaning up Speckle Noise

- Denoising Autoencoder:
  - Task:
    - Denoising speckled images to recover original images
    - Labels: OCT resized dataset
  - Model:
    - Conv2D + ReLU
    - MaxPooling2D
    - UpSampling2D
    - Conv2D + Sigmoid
  - Compile:
    - Optimizer: Adam
    - Loss Function: Mean squared error
    - Learning Rate: 0.001



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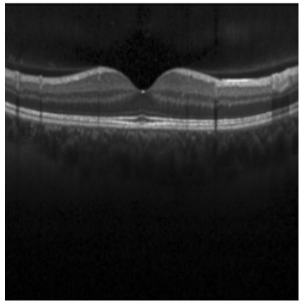
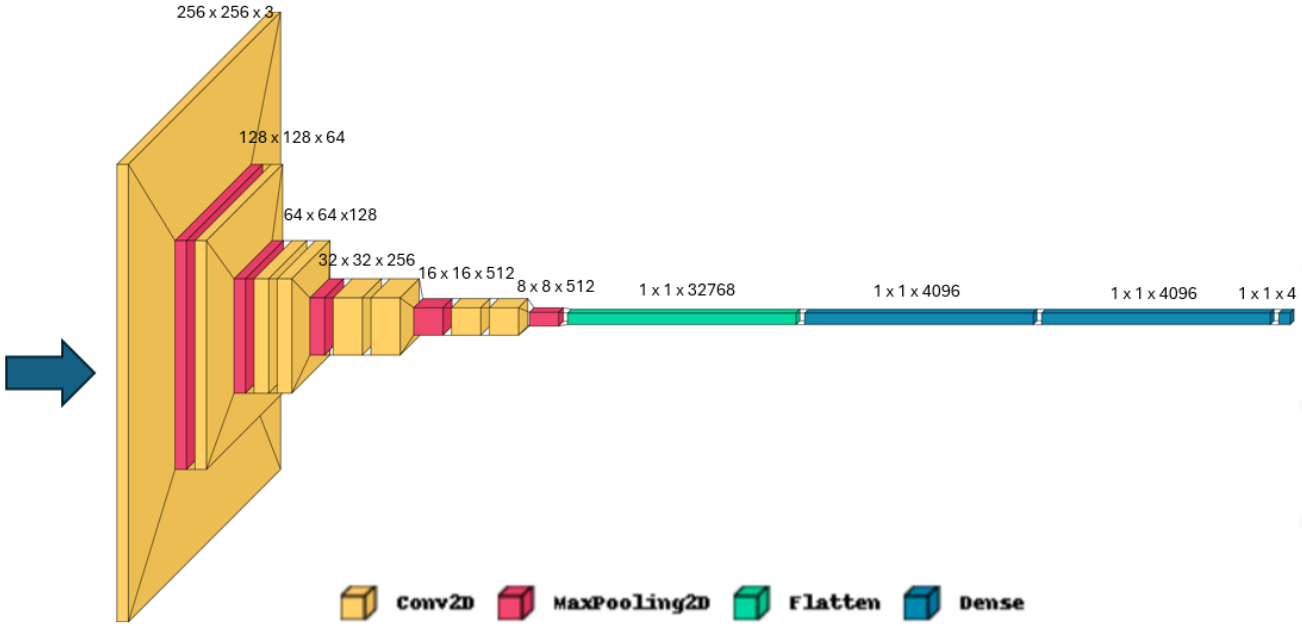
Classification

- VGG-11 model:
  - Task:
    - Multiclass classification
    - Labels:
      - CNV = 1
      - DME = 2
      - DRUSEN = 3
      - NORMAL = 4
  - Model:
    - Conv2D + ReLU
    - MaxPooling2D
    - Fully Connected + ReLU
    - Fully Connected + SoftMax
  - Compile:
    - Optimizer: Adam
    - Loss Function: Categorical cross entropy
    - Learning Rate: 0.001

256 x 256 x 3



Input OCT Image



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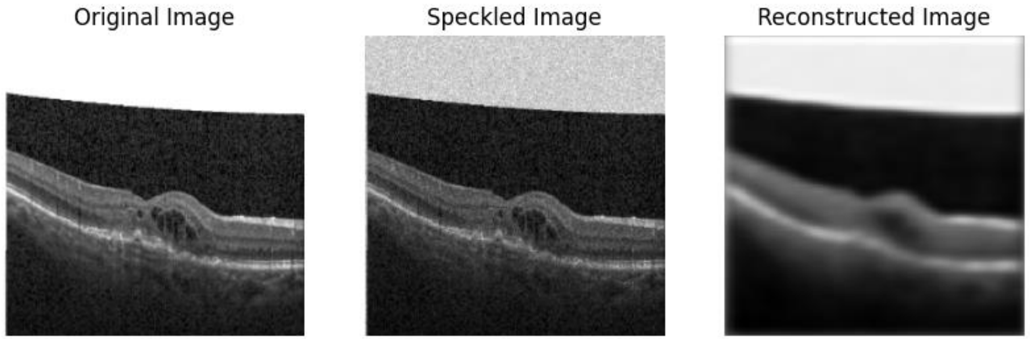
Results

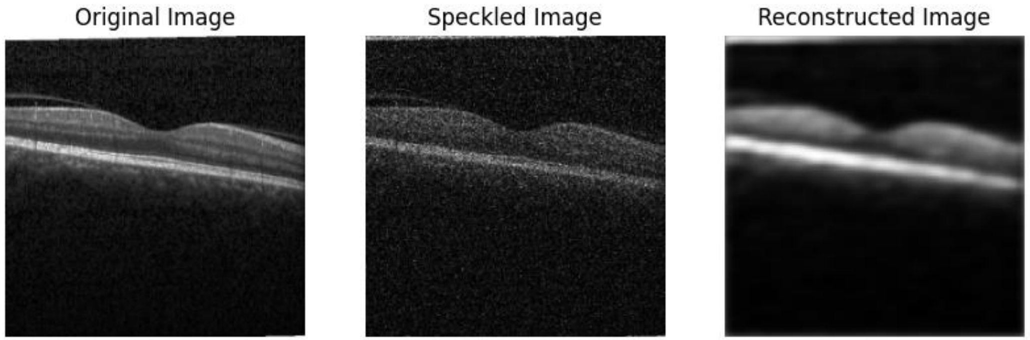
1. Image reconstruction from denoising autoencoder:

Low Speckle Noise:



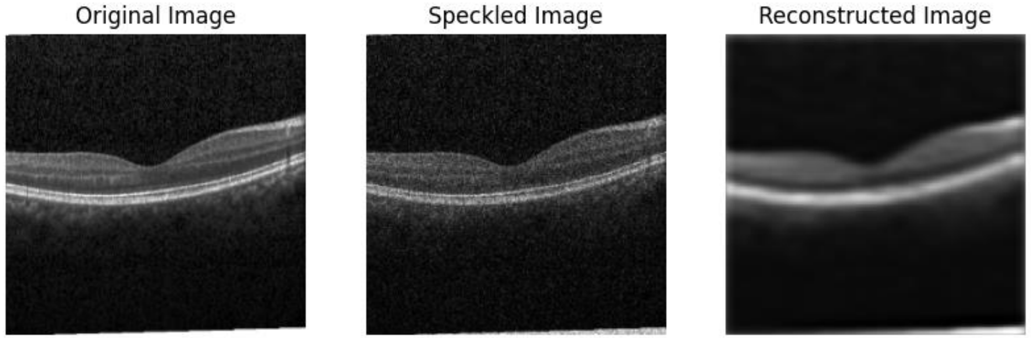
Mean Squared Error = 0.0200

High Speckle Noise:



Mean Squared Error = 0.00670

Medium Speckle Noise:



Mean Squared Error = 0.00512

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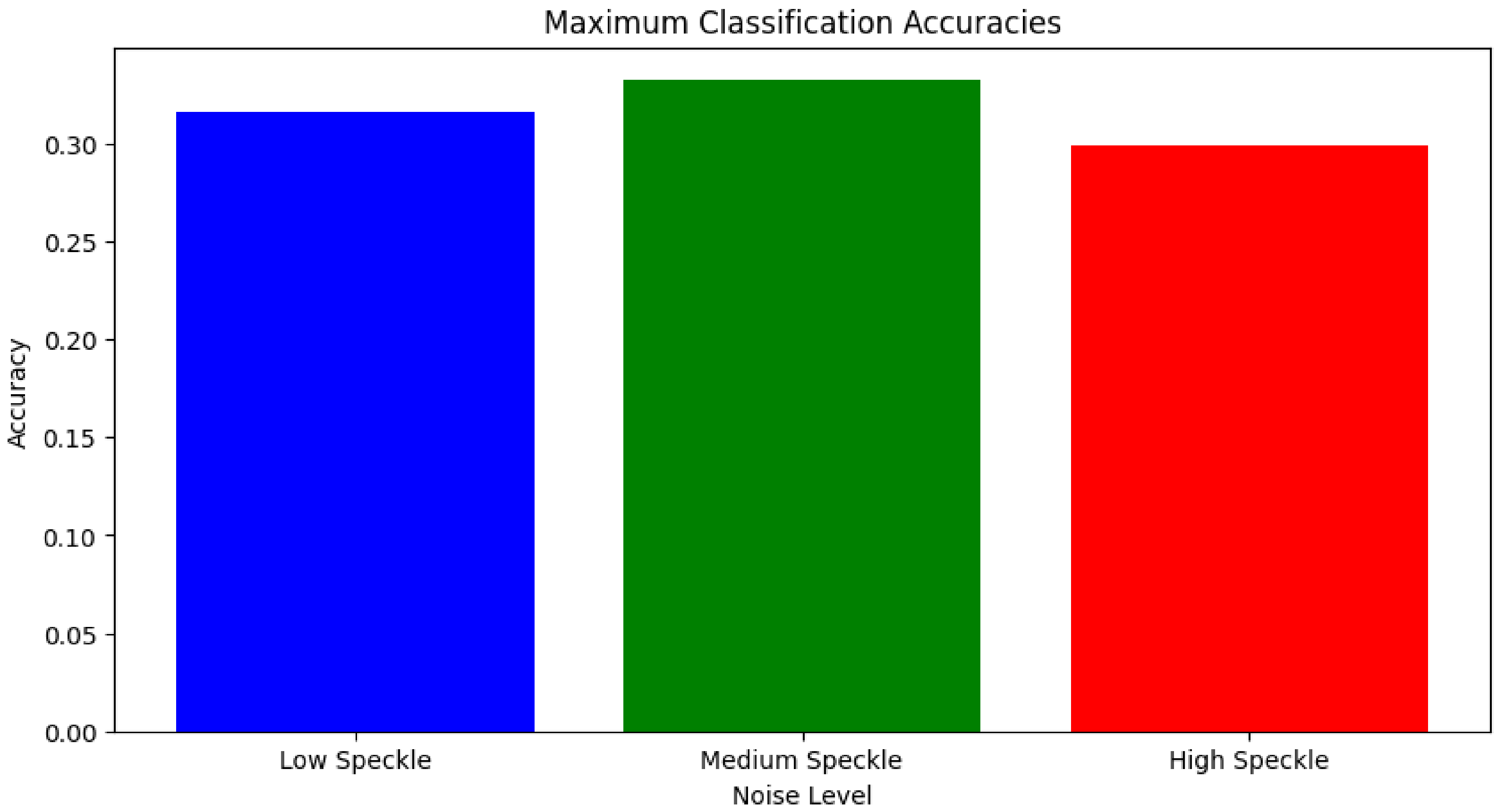
Results

2. Classification Accuracy vs Speckle Noise Level:



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Conclusions

- Denoising autoencoder is effective in removing speckle noise, but causes a strong gaussian blur effect (not ideal for classification)
- Medium speckle noise performs best in terms of speckle noise suppression and classification
- Possible future work:
  - Explore other options for cleaning up speckle noise (e.g., mean filter)
  - Test on dataset with known and predictable speckle noise values
  - Optimize speckle noise (α value) within the CNN itself through a custom layer
  - Test classification on other types of CNN architectures (ResNet, MobileNet, etc.)

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References

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[2] Nabila Eladawi *et al.*, "Optical coherence tomography: A review," pp. 191–221, Jan. 2020, doi: https://doi.org/10.1016/b978-0-12-817440-1.00007-3.

[3] T. Yoneyama and Y. Sakamoto, "Speckle control for electro-holographic display using high-brightness yellow phosphor light source in projector," *Optical engineering*, vol. 62, no. 08, Aug. 2023, doi: https://doi.org/10.1117/1.oe.62.8.083103.

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[5] S. Diao et al., "Classification and segmentation of OCT images for age-related macular degeneration based on dual guidance networks," Biomedical Signal Processing and Control, vol. 84, p. 104810, Jul. 2023. doi:10.1016/j.bspc.2023.104810

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