Visual Intelligence: Lung Cancer Histopathological Classification

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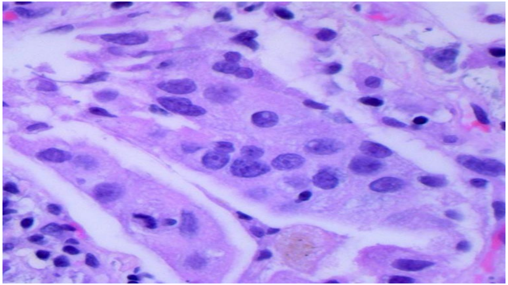
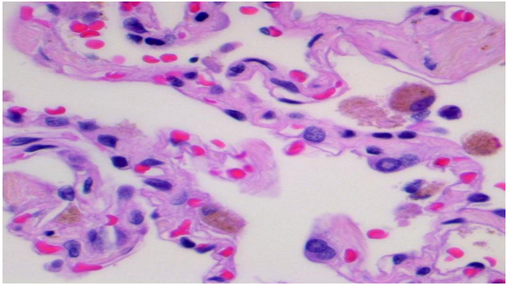
March 2025

Introduction & Problem Statement

- **Dataset**: Lung cancer histopathological images (3 classes):
    - **Adenocarcinoma**
    - **Squamous cell carcinoma**
    - **Benign tissue**
- **Classification Task**: **Binary classification** (adenocarcinoma vs benign tissue)
- **Challenge**: Distinguishing **subtle tissue patterns** and **cellular structures**





Project Goals

- Compare **traditional CNN** vs **ScatNet** approaches (in particular for feature extraction)
- Achieve **high accuracy** with **interpretable results**
- Apply **explainable AI techniques** to validate model decisions, in particular:
  - **Attribution analysis** with **guided backpropagation**
  - **Filter analysis** to understand learned patterns

Data Preprocessing & Setup

- **Dataset Organization**:
  - **K-fold cross-validation** with 10 folds
  - Class distributions already balanced
  - Image size kept at **768×768 pixels**
  - **Grayscale conversion** for analysis

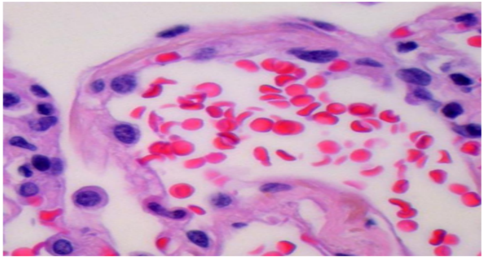
Key Finding

Using grayscale images for analysis because with only color images, the model achieved high accuracy by learning **color distributions**

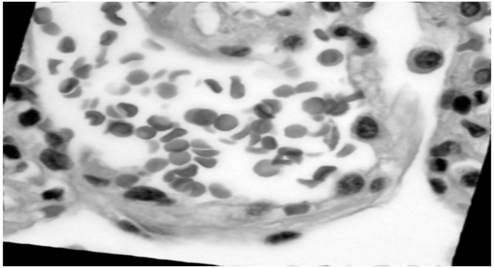
Preprocessing Pipeline

- Image **normalization** and **standardization** for each fold
- The dataset already includes augmentation, but I added some more:
  - Random rotations
  - Random flips
  - Color jittering
  - Random cropping
  - Gaussian noise

benign



Augmented benign image

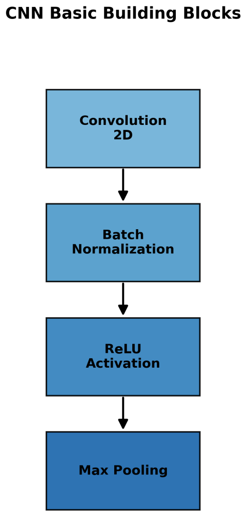


CNN Model Architecture

- **Efficient Feature Extraction Design**:
  - Similar to **ResNet architecture** without skip connections
  - Three progressive convolutional blocks (16→16→24 filters)
  - First convolutional layer with **11×11 kernel**
  - Strategic dimensionality reduction via **max pooling**
  - **Batch normalization** for improved training stability
  - **ReLU activations** for non-linear patterns

Key Findings

- Achieves **exceptional classification accuracy** despite minimal parameters
- First layer filters may not appear visually interpretable with small learning rates



CNN Architecture Details

```
CNNImageClassifier(
  (features): Sequential(
    (0): Conv2d(1, 16, kernel_size=(11, 11), stride=(2, 2))
    (1): BatchNorm2d(16)
    (2): ReLU()
    (3): MaxPool2d(kernel_size=2, stride=2)
    ...
  )
  (classifier): FeatureClassifier(
    (fc1): Linear(384, 16)
    (bn): BatchNorm1d(16)
    (relu): ReLU()
    (do): Dropout(p=0.5)
    (fc2): Linear(16, 2)
  )
)
```

- Total parameters: **14,090**
- Model size: **52.58MB**
- **Efficient architecture** with minimal parameters

```
ScatNetImageClassifier(
  (scattering): Scattering2D()
  (global_pool): AdaptiveAvgPool2d(4, 4)
  (classifier): FeatureClassifier(
    (fc1): Linear(3472, 16)
    ...
  )
)
```

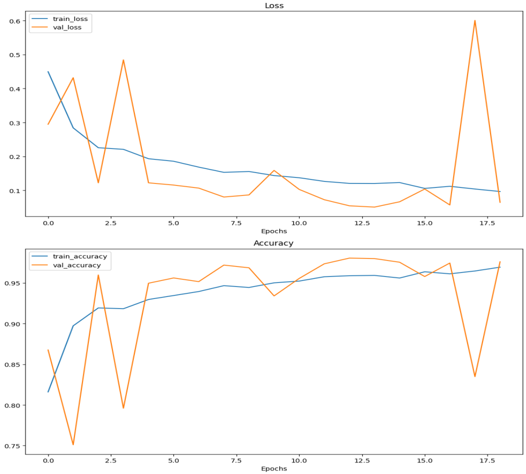
- **Wavelet-based feature extraction**:
  - **J=3** scale parameter for wavelet decomposition
  - **L=8** orientations, **M=2** scattering order
  - **Translation**, **rotation**, and **scaling invariant**

Key Finding

Requires **more complex classifier** layer for good performance

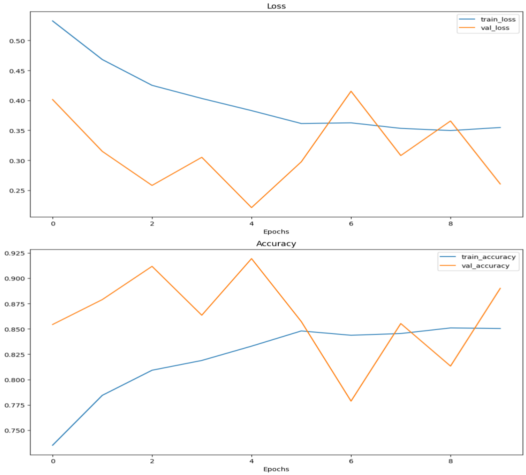
CNN Learning Curves Analysis

- **Rapid convergence** within 15 epochs
- **Consistent performance** across folds
- **Limited overfitting** due to effective regularization
- Final validation accuracy around **99%**



ScatNet Learning Curves Analysis

- **Slower convergence** but fewer epochs needed
- **More complex classifier** needed
- **Greater performance variation** across folds



Metric	CNN	ScatNet
Mean Accuracy	**99.26% $\pm$ 0.72%**	**92.99% $\pm$ 1.59%**
Mean F1 Score	**99.27% $\pm$ 0.72%**	**92.83% $\pm$ 1.70%**
Accuracy Range	**97.70% - 99.90%**	**89.10% - 95.10%**
Training Speed	**Faster**	**Slower**

Key Performance Findings

- CNN **significantly outperforms** ScatNet (by **6.27%**)
- K-fold validation confirms **robust performance**
- CNN shows **less variance** between folds
- CNN achieves convergence in **fewer epochs**

Performance Range:

- Accuracy: **98.00%** - **99.90%** across all folds
- F1 Score: **98.01%** - **99.90%** across all folds
- Most consistent fold: **Fold 9** (99.90% accuracy)
- All folds achieved $>$**97.70% accuracy**

Overall Statistics:

- Mean Accuracy: **99.26%**
- Mean F1 Score: **99.27%**
- Standard Deviation: **0.72%**

Performance Range:

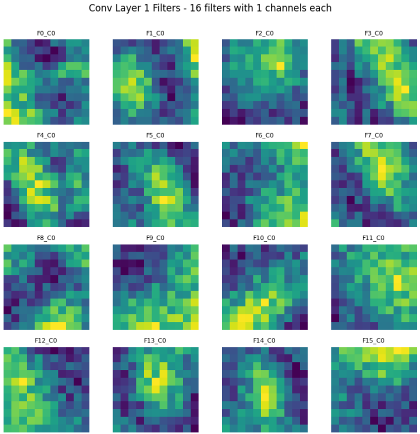
- Accuracy: **89.10% - 95.10%** across all folds
- F1 Score: **88.68% - 95.06%** across all folds
- Best performing fold: **Fold 6** (95.10% accuracy)
- Worst performing fold: **Fold 1** (89.10% accuracy)

Overall Statistics:

- Mean Accuracy: **92.99%**
- Mean F1 Score: **92.83%**
- Standard Deviation: **1.59%**

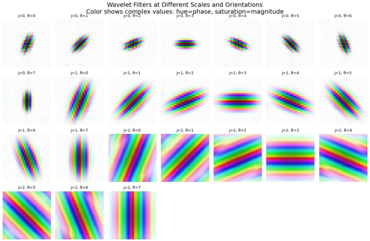
CNN Filter Analysis

- **Detected Filter Patterns**:
  - **Diagonal/Vertical Strips**: Detect edges, gaps, and transitions between textures
  - **Circular Points**: Identify spots, blobs, and localized features
  - **Two-Part Filters**: Capture gradients and contrast changes
- **Filter Implications**:
  - Learning localized and structured features
  - Capturing directional patterns and contrast
  - Detecting orientation-dependent structures

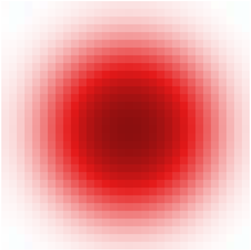


ScatNet Filter Analysis

- **Pre-defined wavelet transforms** (not learned)
- **Scale and rotation invariant** features
- **Lower discriminative power** despite theoretical advantages
- Fixed mathematical representation **limits adaptability**
- Data augmentation impact: **less significant**

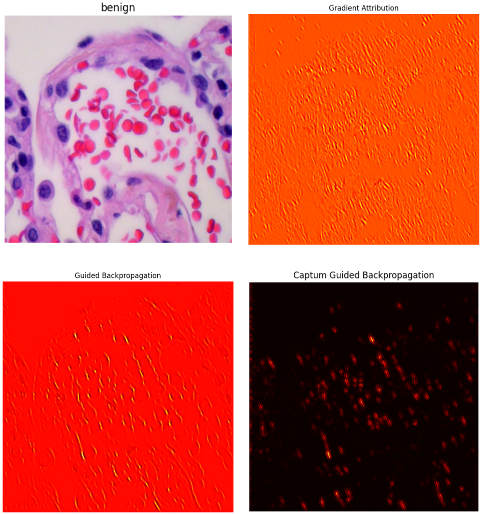


The corresponding low-pass filter, also known as scaling function.



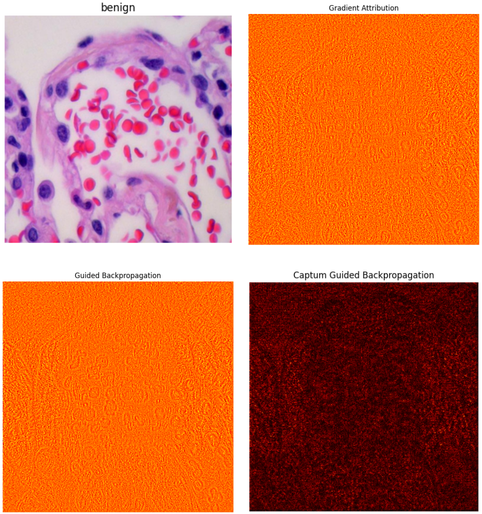
CNN Attribution Analysis

- Visualizes regions **most influential** for classification
- **Guided backpropagation** significantly reduces noise compared to regular backpropagation
- **Higher resolution** feature attribution with clearer patterns
- Captum implementation shows **similar patterns** despite different color scaling
- **Strong correlation** with pathological markers across all methods



ScatNet Attribution Analysis

- **Minimal differences** between guided and regular backpropagation
- Limited impact of guided backprop due to **ReLU only in classifier**
- **Non-recognizable patterns** in guided backprop visualization
- Attribution shows **diffuse, less interpretable regions**
- **Less coherent** with pathological indicators



Key Insights

- **Color features** are not crucial for lung cancer histopathology classification
- **Learned features** (CNN), in this scenario, are more effective than **pre-defined features** (ScatNet)
- **CNN** are harder to train but yield **better performance**

Thank you for your attention

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