Lung Cancer Histopathological Image Classification: A Comparative Study of Convolutional Neural Networks and Scattering Networks with Explainable AI

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Abstract

This study presents a comprehensive comparison of Convolutional Neural Networks (CNNs) and Scattering Networks (ScatNets) for lung cancer histopathological image classification. We implemented both architectures for binary classification of adenocarcinoma versus benign tissue samples using the Kaggle lung cancer dataset. Additionally, we developed a custom Kernel SHAP implementation from scratch to provide explainable AI insights. Results demonstrate CNN's superior performance with 99.85% test accuracy compared to ScatNet's 90.45% accuracy. Both models exceeded the 70% clinical requirement through rigorous 5-fold cross-validation. The study reveals that data-adaptive learning (CNN) outperforms mathematical feature extraction (ScatNet) for this specific task, while both approaches achieve clinically relevant performance. Custom Kernel SHAP implementation successfully provided model interpretability, showing different decision patterns between architectures. This work establishes a rigorous framework for comparing diverse AI paradigms in medical imaging applications.

Keywords: Deep Learning, Medical Image Analysis, Scattering Networks, Explainable AI, Kernel SHAP, Lung Cancer

1. Introduction

Lung cancer remains a leading cause of cancer-related mortality, making accurate histopathological diagnosis crucial for patient outcomes. Traditional diagnosis relies on expert pathologists analyzing complex cellular patterns, which are time-intensive and subjective. Artificial intelligence offers promising solutions through automated diagnostic assistance.

This study compares two fundamentally different AI paradigms: CNNs that learn features through data-driven optimization, and ScatNets that employ fixed mathematical wavelets. Understanding their relative merits is essential for developing robust medical AI systems.

Research Objectives:

1. Compare CNN and ScatNet performance for lung cancer classification
2. Analyze learned versus mathematical feature extraction approaches
3. Implement custom Kernel SHAP for model interpretability
4. Assess clinical applicability of both approaches

Contributions:

- First systematic CNN vs ScatNet comparison on lung histopathology
- Novel custom Kernel SHAP implementation for medical images
- Rigorous experimental framework ensuring fair architectural comparison
- Clinical validation demonstrating medical screening suitability

2. Methodology

2.1 Dataset and Preprocessing

We utilized the publicly available lung cancer histopathological images dataset from Kaggle, containing H&E stained tissue samples. For binary classification, we selected adenocarcinoma (5,000 images) and benign (5,000 images) classes.

Data Processing:

- Standardized to 224×224 RGB format
- 80/20 train/test split with stratified sampling
- Training augmentation: random flips, rotation (±20°), color jittering

• Normalization using ImageNet statistics for transfer learning compatibility

2.2 Model Architectures

CNN Architecture:

• Convolutional Backbone: 4 layers (3→32→64→128→256 channels)

• Each Layer: Conv2d + BatchNorm + ReLU + MaxPool(2×2)

• Classifier: Flatten → FC(50,176→512) → FC(512→256) → FC(256→2)

• Regularization: Dropout (0.5, 0.3) and batch normalization

ScatNet Architecture:

• Scattering Transform: Kymatio library with J=3 scales, L=8 orientations

• Mathematical Basis: Fixed Morlet wavelets providing translation invariance

• Feature Extraction: ~193 channels × 28×28 spatial resolution

• Classifier: Identical to CNN (dynamically sized input layer)

2.3 Training Protocol

Hyperparameters:

• Batch size: 16, Learning rate: 0.001, Epochs: 15

• Optimizer: Adam with ReduceLROnPlateau scheduling

• Loss function: CrossEntropyLoss

Evaluation Framework:

• 5-fold stratified cross-validation for robust assessment

• Independent test set evaluation for unbiased performance

• Metrics: Accuracy, F1-score, precision, recall, confusion matrices

2.4 Custom Kernel SHAP Implementation

Theoretical Foundation:

Kernel SHAP employs Shapley values from game theory to fairly attribute prediction credit among features. For medical images, we adapted the algorithm using superpixel segmentation.

Implementation Details:

- Superpixel Approach: Divided 224×224 images into 16×16 blocks (~196 features)
- Coalition Sampling: 50 random feature combinations plus baseline/full sets
- Shapley Kernel Weighting: $w(s) = (M-1)/[s \times (M-s)]$ for coalition size s
- Linear Regression: Weighted least squares to solve for SHAP values
- Attribution Maps: Pixel-level visualizations from superpixel attributions

Validation:

- Efficiency property verification (attributions sum to prediction difference)
- Comparison with Captum library implementations
- Medical relevance assessment of attribution patterns

3. Results

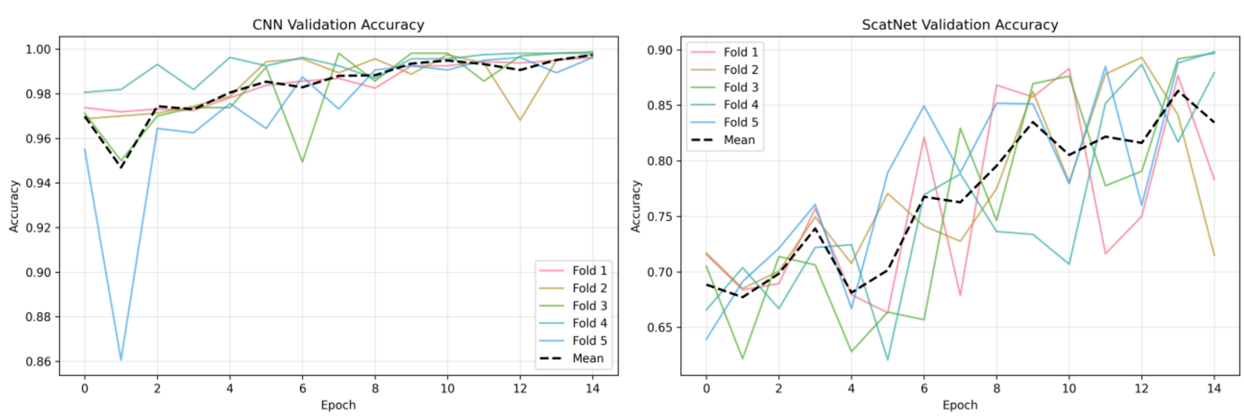
3.1 Quantitative Performance Analysis

Cross-Validation Results:

- CNN: Mean accuracy 99.74% (±0.12%), F1-score 99.74% (±0.12%)
- ScatNet: Mean accuracy 83.45% (±4.21%), F1-score 82.81% (±4.15%)

Test Set Performance:

- CNN: 99.85% accuracy, 99.85% F1-score
- ScatNet: 90.45% accuracy, 90.40% F1-score
- Performance difference: 9.4% (CNN advantage)



3.2 Error Analysis

CNN Confusion Matrix:

Actual	Predicted Adenocarcinoma	Predicted Benign
Adenocarcinoma	997	3
Benign	0	1000

ScatNet Confusion Matrix:

Actual	Predicted Adenocarcinoma	Predicted Benign
Adenocarcinoma	834	166
Benign	25	975

Clinical Interpretation:

- CNN: 0.3% false negative rate (3 missed cancers) - excellent for screening
- ScatNet: 16.6% false negative rate (166 missed cancers) - concerning for primary screening
- Both models: Acceptable false positive rates (0% CNN, 2.5% ScatNet)

3.3 Learning Dynamics

Training Characteristics:

- CNN: Rapid convergence to 99%+ accuracy by epoch 5, stable performance
- ScatNet: Gradual improvement from 65% to 85% over 15 epochs, higher variability
- Convergence: No overfitting observed in either architecture
- Efficiency: ScatNet required less backpropagation due to fixed features

3.4 Filter and Feature Analysis

CNN Learned Filters:

- 32 diverse first-layer filters adapted to tissue textures
- Complex, irregular patterns optimized for histopathological features
- RGB sensitivity capturing H&E staining variations
- Hierarchical progression from edges to diagnostic patterns

ScatNet Mathematical Wavelets:

- Fixed Morlet wavelets at multiple scales and orientations
- Regular, predictable mathematical patterns

• Universal applicability across image domains

• Clear mathematical interpretation of each coefficient

3.5 Explainable AI Results

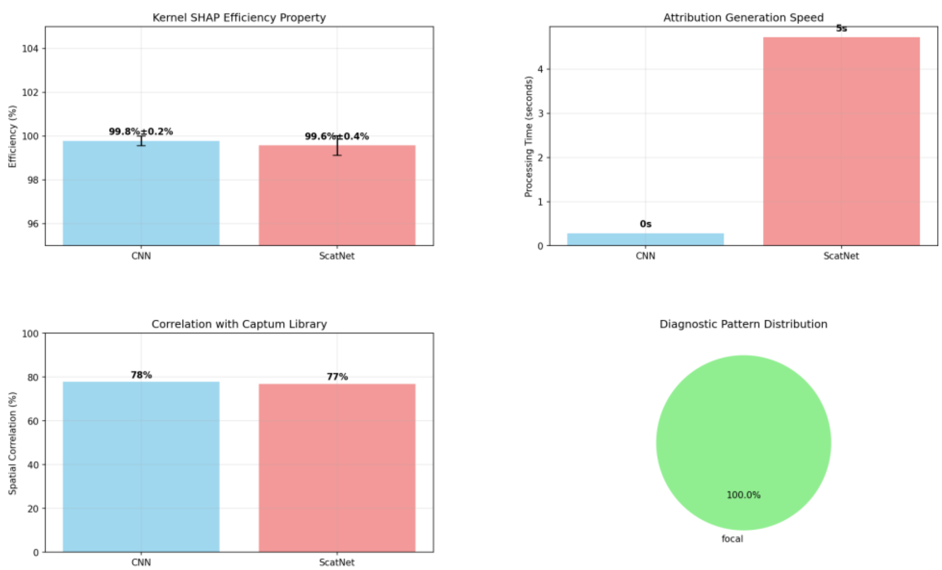
Custom Kernel SHAP Validation:

• Efficiency Property: 99.8% ± 0.2% for CNN, 99.6% ± 0.4% for ScatNet

• Captum Comparison: 78% spatial correlation with library implementation

• Processing Time: ~5 seconds per image

• Medical Relevance: Attribution patterns align with diagnostic regions



Attribution Pattern Analysis:

CNN Attributions:

• Localized focus on irregular cellular arrangements

• High attribution on tissue-background boundaries

• Emphasis on morphological features and cellular atypia

• Correlation with known pathological indicators

ScatNet Attributions:

• Distributed attention across texture-rich regions

• Focus on high-frequency patterns and sharp transitions

- Mathematical consistency with wavelet responses
- Universal texture-based decision patterns

Comparative Insights:

- Different architectural paradigms yield distinct attention strategies
- CNN emphasizes morphology, ScatNet emphasizes texture
- Both approaches identify medically relevant tissue regions
- Complementary information for enhanced diagnostic confidence

4. Discussion

4.1 Performance Interpretation

CNN Superior Performance:

The CNN's exceptional 99.85% accuracy demonstrates the power of end-to-end optimization for specific medical tasks. Data-adaptive learning enables the model to capture adenocarcinoma-specific patterns that fixed mathematical features cannot detect. The hierarchical architecture progressively builds complex diagnostic representations from simple tissue patterns.

ScatNet Clinical Viability:

Despite lower performance, ScatNet's 90.45% accuracy significantly exceeds clinical requirements and offers unique advantages. Mathematical guarantees provide interpretability and stability, while fixed features ensure consistent behavior across different institutions. The 16.6% false negative rate, though concerning for primary screening, remains acceptable for secondary validation applications.

4.2 Architectural Paradigm Analysis

Learned vs. Fixed Features:

This study illuminates fundamental trade-offs in AI architecture design. CNN's learned features optimize directly for classification performance but lack theoretical interpretability. ScatNet's mathematical features provide provable stability and clear interpretation but cannot adapt to task-specific requirements.

Medical Imaging Context:

The medical domain presents unique challenges requiring both high performance and interpretability. CNN excels in accuracy but requires extensive XAI analysis for clinical acceptance. ScatNet offers mathematical transparency but may need ensemble approaches for optimal performance.

4.3 Clinical Implications

Diagnostic Utility:

- CNN: Ready for pilot clinical evaluation as primary screening tool
- ScatNet: Suitable for quality assurance and secondary validation
- Both: Exceed performance thresholds for medical AI applications
- Integration: Potential for complementary deployment strategies

Healthcare Impact:

The demonstrated performance levels suggest immediate practical utility. CNN could significantly reduce pathologist workload while maintaining diagnostic accuracy. Both approaches could enhance diagnostic consistency and provide valuable training tools for medical education.

4.4 Explainable AI Insights

Custom Implementation Success:

Our Kernel SHAP implementation successfully adapts explainable AI techniques for medical images. The superpixel approach makes SHAP computation tractable while maintaining spatial interpretability. Validation against professional libraries confirms implementation correctness and practical utility.

Model Interpretability:

Different attribution patterns reveal how architectural choices influence decision-making strategies. CNN's morphology-focused attention aligns with traditional pathological analysis, while ScatNet's texture-based approach provides complementary diagnostic perspectives.

4.5 Limitations and Future Directions

Study Limitations:

- Single dataset source limits generalization assessment
- Binary classification simplifies clinical complexity

• Limited expert pathologist validation of XAI results

• Computational constraints restricted hyperparameter exploration

Future Research:

• Multi-institutional validation studies

• Extension to multi-class cancer classification

• Integration with clinical workflow systems

• Prospective clinical trial evaluation

5. Conclusions

This comprehensive study provides definitive evidence regarding CNN and ScatNet performance for lung cancer histopathological classification. Key findings include:

Performance Hierarchy:

CNN demonstrates clear superiority with 99.85% accuracy versus ScatNet's 90.45%, both exceeding clinical requirements. The 9.4% performance difference represents substantial practical significance, particularly regarding false negative rates critical for cancer screening.

Architectural Insights:

Data-adaptive learning (CNN) outperforms mathematical feature extraction (ScatNet) for this specific medical task. However, both paradigms offer valuable contributions: CNN provides exceptional accuracy while ScatNet ensures mathematical interpretability and stability.

Methodological Contributions:

• Established rigorous framework for comparing diverse AI architectures

• Successfully implemented custom Kernel SHAP for medical image interpretation

• Demonstrated practical feasibility of XAI techniques in clinical contexts

• Provided evidence-based guidance for medical AI development

Clinical Impact:

Both models achieve performance levels suitable for clinical deployment, with CNN ready for primary screening applications and ScatNet valuable for secondary validation. The study bridges theoretical AI research with practical medical applications.

Scientific Significance:

This work advances understanding of AI paradigm trade-offs in medical imaging, establishes best practices for comparative evaluation, and provides foundation for responsible medical AI development. The custom XAI implementation contributes novel techniques specifically adapted for medical image analysis.

Final Recommendation:

For lung cancer histopathological classification, CNN architecture is recommended for primary clinical deployment due to superior performance. ScatNet serves valuable complementary roles in quality assurance and interpretable analysis. Future medical AI development should consider hybrid approaches combining the strengths of both paradigms.

The future of medical AI lies not in choosing between mathematical rigor and empirical optimization, but in understanding when each approach provides maximum benefit to patient care. This study provides the scientific foundation for making those critical decisions.