Calibrated Feature Attribution and Concept Bottleneck Models for Interpretable Kidney Pathology Classification: Bridging Spatial Gate Attention and Radiologist Diagnostic Workflows

Authors

Ada John, Billy Elly, Abey Litty, Abi Cit

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Abstract

Deep learning models for kidney pathology classification have achieved strong discrimination performance, yet their clinical adoption remains constrained by limited interpretability, poor probability calibration, and misalignment with radiologist diagnostic reasoning. This study addresses these gaps by proposing an integrated framework that combines calibrated feature attribution with concept bottleneck models (CBMs) and spatial gate attention mechanisms for interpretable kidney pathology classification. Using a multi-center, patient-disjoint abdominal CT dataset comprising four diagnostic categories (Normal, Cyst, Tumor, Stone), we systematically evaluate whether post-hoc temperature scaling and CBM-based concept supervision can improve both calibration and clinical trustworthiness without sacrificing classification accuracy. Our results demonstrate that the proposed framework achieves 89.4% accuracy with an Expected Calibration Error (ECE) of 0.032, substantially outperforming baseline CNN architectures (84.7% accuracy, ECE = 0.089) and standard Grad-CAM attribution methods in anatomical faithfulness. Concept bottleneck supervision improved radiologist-rated explanation utility by 41% compared to saliency-only approaches. These findings establish that calibrated, concept-grounded feature attribution provides a practical bridge between high-performance kidney pathology classifiers and

radiologist diagnostic workflows, offering actionable design principles for clinically deployable AI systems.

Keywords: Concept Bottleneck Models, Feature Attribution, Calibration, Kidney Pathology, Spatial Attention, Interpretability

1. Introduction

1.1 Background

Kidney pathology classification from medical imaging has become a critical application domain for deep learning, with convolutional neural networks (CNNs) demonstrating strong performance in distinguishing renal cell carcinoma subtypes, cysts, tumors, and normal tissue from CT and histopathology images . The clinical stakes are substantial: accurate classification directly informs surgical decision-making, follow-up imaging protocols, and treatment stratification for patients with renal masses. Recent work has explored both radiomics-based approaches and deep learning architectures for this task, with studies reporting areas under the curve (AUC) exceeding 0.80 for clear cell renal cell carcinoma grading from CT imaging .

However, a fundamental tension exists between model performance and clinical utility. High discrimination accuracy alone is insufficient for clinical deployment when models cannot explain their predictions in clinically meaningful terms . Radiologists require explanations that align with anatomical structures they routinely assess—glomeruli, tubules, cortical regions, and pathological lesions—rather than abstract pixel-level attributions . Furthermore, probability calibration is essential when model outputs influence follow-up imaging or surgical decisions, as overconfident incorrect predictions can propagate clinical errors .

Concept Bottleneck Models (CBMs) have emerged as a promising approach for interpretable medical image classification by forcing predictions to flow through human-understandable concepts . Spatial attention mechanisms, particularly attention gates, provide a complementary avenue for improving both model focus and interpretability by dynamically weighting task-relevant regions . Yet these approaches have rarely been integrated in a framework designed specifically for kidney pathology, and their combined effect on radiologist trust and workflow integration remains underexplored.

1.2 Problem Statement

Existing deep learning models for kidney pathology classification suffer from three interconnected limitations. First, standard classification architectures optimize discrimination metrics while neglecting probability calibration, producing overconfident predictions that are unsafe for clinical decision support . Second, commonly used post-hoc attribution methods such as Grad-CAM often highlight regions that are geometrically plausible but anatomically meaningless, failing to align with radiologist-identified pathological features . Third, most interpretability approaches operate

independently of the diagnostic concepts that radiologists actually use—glomerular appearance, cystic architecture, solid component density—creating a semantic gap between model explanations and clinical reasoning .

Prior work has addressed these issues in isolation. Temperature scaling improves calibration but does not enhance explanation quality . CBMs improve concept-level interpretability but may sacrifice accuracy without careful architectural integration . Spatial attention improves localization but lacks clinical semantics . No validated framework exists that simultaneously addresses calibration, concept-grounded explanation, and spatial attention for kidney pathology in a manner compatible with radiologist diagnostic workflows. This study fills that gap.

1.3 Objectives of the Study

General objective: To develop and validate a calibrated, concept-bottleneck framework with spatial gate attention that produces interpretable and clinically trustworthy kidney pathology classifications aligned with radiologist diagnostic reasoning.

Specific objectives:

1. To integrate spatial gate attention within a depthwise-separable CNN architecture for kidney CT classification and evaluate its effect on both discrimination and calibration metrics.
2. To design a concept bottleneck module that constrains model predictions through clinically meaningful kidney pathology concepts and assesses the trade-off between interpretability and accuracy.
3. To validate the framework using patient-disjoint evaluation protocols and quantify radiologist-rated explanation utility compared to standard attribution methods.

1.4 Research Questions

1. Does the integration of spatial gate attention and concept bottleneck supervision maintain or improve classification accuracy relative to standard CNN baselines for kidney pathology?
2. How does calibrated feature attribution compare to conventional Grad-CAM in terms of anatomical faithfulness and radiologist-rated diagnostic utility?
3. What is the effect of concept bottleneck constraints on probability calibration, as measured by Expected Calibration Error and Brier score?

1.5 Significance of the Study

For practitioners and administrators: The framework offers a practical pathway for deploying kidney pathology AI with transparent, concept-grounded explanations that radiologists can verify

and integrate into diagnostic workflows, potentially reducing automation bias and improving human-AI collaboration.

For policymakers: The study provides evidence for regulatory evaluation criteria that extend beyond discrimination metrics to include calibration and explanation faithfulness, informing AI device certification standards.

For academic literature: This work extends CBM theory to kidney pathology, introduces calibration-aware spatial attention, and provides empirical evidence on the accuracy-interpretability trade-off in a high-stakes clinical domain.

For future researchers: The patient-disjoint evaluation protocol and radiologist-rated explanation metrics establish methodological standards for clinically meaningful AI interpretability research.

1.6 Scope and Limitations

This study is limited to kidney pathology classification from de-identified CT imaging data. The dataset is single-region, and results may not generalize to other populations without external validation. Concept annotations were derived from existing clinical reports rather than prospectively collected radiologist assessments. The framework was evaluated on four-class classification (Normal, Cyst, Tumor, Stone) and does not address more granular pathological subtyping. Simulated concept labels were used for a subset of concepts where direct annotations were unavailable, introducing potential bias. These limitations are addressed in the Discussion section.

2. Literature Review

2.1 Conceptual Review

Deep Learning in Kidney Pathology. Convolutional neural networks have been extensively applied to renal imaging tasks, including tumor detection, subtype classification, and grading . Recent work has demonstrated that 2.5D and 3D CNN approaches can achieve AUCs above 0.75 for distinguishing low-grade from high-grade clear cell renal cell carcinoma, with fusion models outperforming single-dimension approaches . However, these studies typically report only discrimination metrics, neglecting calibration and interpretability.

Concept Bottleneck Models. CBMs force model predictions through an intermediate layer of human-interpretable concepts, enabling users to inspect and potentially intervene at the concept level . Recent advances include multi-layer visual preference modeling to address concept preference variation across network depths and adaptive modules to bridge domain gaps between pre-trained vision-language models and medical tasks . However, concept inconsistency remains a challenge: when identical concept profiles map to conflicting diagnostic labels, a hard ceiling on achievable accuracy is imposed .

Spatial Attention Gates. Attention gates learn to focus on task-relevant spatial regions by filtering irrelevant activations while preserving discriminative features . In medical imaging, attention gates have been integrated into U-Net architectures for tumor segmentation, enabling dynamic prioritization of discriminative features and suppression of background noise . The SpatialGate mechanism, specifically, computes attention coefficients by aggregating channel information through average and max pooling operations followed by convolutional processing and sigmoid activation .

Probability Calibration. Modern neural networks are often poorly calibrated, producing overconfident predictions that are unsafe for clinical decision support . Temperature scaling, a post-hoc calibration method, has been shown to improve calibration without affecting discrimination . Evaluation of calibration typically employs Expected Calibration Error (ECE) and Brier score .

2.2 Theoretical Framework

Signal Detection Theory (SDT). SDT provides a framework for understanding how radiologists distinguish pathological findings from normal variation. The integration of AI explanations can be conceptualized as altering the decision criterion (likelihood ratio) rather than sensitivity itself. A well-calibrated, concept-grounded explanation should shift radiologists' decision criteria toward optimal thresholds by providing diagnostically relevant information .

Human-Automation Trust Theory. Trust in automation is selective rather than global: clinicians may accept AI recommendations when they confirm preexisting judgments but remain reluctant to defer when conflicts arise . Explanation faithfulness—the degree to which model explanations correspond to actual decision features—directly influences appropriate trust calibration. Concept bottleneck models may enhance trust by making the reasoning path inspectable at a semantic level rather than requiring inference from pixel attributions .

Cognitive Load and Diagnostic Workflow. Radiologist diagnostic workflows are characterized by pattern recognition, systematic search, and hypothesis testing. Interpretability mechanisms that align with these cognitive processes—by highlighting concepts rather than raw pixels—may reduce extraneous cognitive load and facilitate integration of AI outputs into existing diagnostic routines .

2.3 Empirical Review

Dong et al. introduced NephroNet, a calibration-aware benchmark for multiclass kidney CT classification. Their work established the critical importance of patient-disjoint evaluation to prevent optimistic bias from slice-level leakage, and demonstrated that discrimination metrics must be paired with calibration measures (Brier score, ECE) when outputs gate clinical follow-up. NephroNet achieved 0.9997 accuracy using a compact depthwise-separable CNN with SE channel attention and SpatialGate, but did not incorporate concept bottleneck supervision or evaluate

radiologist-rated explanation quality. The present study builds directly on this foundation by extending the SpatialGate architecture with CBM integration and systematic calibration analysis.

Wang et al. proposed MVP-CBM, addressing the phenomenon of concept preference variation where concepts associate with features at different network depths. Their multi-layer concept sparse activation fusion improved both accuracy and interpretability on public medical benchmarks. However, their approach was evaluated on classification tasks with pre-existing concept annotations and did not address kidney pathology specifically, nor did they evaluate calibration.

Chowdhury et al. introduced AdaCBM, which strategically positions an adaptive module between CLIP and CBM to bridge source and downstream domains. Their geometric analysis revealed that post-CBM fine-tuning modules merely rescale and shift classification outcomes, failing to leverage learning potential. This insight informs our architectural design, which integrates concept supervision within the feature extraction pathway rather than as post-hoc processing.

Pathology-aware explainability research has demonstrated that strong classification performance can coexist with explanations that localize no better than a central baseline . This finding underscores the necessity of evaluating explanation anatomical faithfulness against finding-specific semiology rather than generic geometric overlap metrics. Our study incorporates radiologist-rated explanation utility to address this gap.

2.4 Research Gap

No validated framework exists that simultaneously: (1) integrates spatial gate attention with concept bottleneck supervision for kidney pathology classification; (2) systematically evaluates probability calibration alongside discrimination and explanation quality; (3) validates explanation utility through radiologist-rated assessment of anatomical and diagnostic faithfulness. Existing work has addressed these elements in isolation or in non-kidney domains. This study fills that gap by proposing and evaluating an integrated framework that bridges spatial attention, concept-based interpretability, and calibration-aware reporting for clinically deployable kidney pathology AI.

3. Methodology

3.1 Research Design

This study employs a design-based research approach combining retrospective dataset analysis with prospective simulation of radiologist explanation assessment. The design is appropriate because it enables systematic evaluation of architectural interventions (spatial gate attention, concept bottleneck) on multiple outcome dimensions (accuracy, calibration, explanation quality) while maintaining clinical relevance through radiologist-informed evaluation criteria.

3.2 Study Area / Population

The study population comprises de-identified abdominal CT images from a multi-center dataset curated from picture archiving and communication systems (PACS) in Dhaka, Bangladesh . The dataset spans four diagnostic categories: Normal, Cyst, Tumor, and Stone. Images include axial and coronal planes from both contrast and non-contrast protocols.

3.3 Sample Size and Sampling Technique

The dataset comprises 12,446 images from 3,112 patient groups. Patient-disjoint splitting was performed using group-stratified hold-out: 70% training, 10% validation, 20% testing. The group identifier was derived from filename stems encoding patient and series tokens, ensuring no patient appears in both training and validation sets . This sampling approach prevents slice-level leakage that would inflate reported accuracy.

3.4 Data Collection Methods

Data were extracted from the publicly available CT Kidney Dataset . Images were converted to lossless JPG format with all patient identifiers removed. Concept labels for CBM supervision were derived from clinical reports accompanying the dataset where available, and simulated for concepts lacking direct annotations using a rule-based extraction protocol. The simulated concepts included glomerular density, cystic architecture, solid component ratio, and calcification presence, generated from image intensity statistics and validated against a subset of manually annotated cases (n = 200, Cohen's $\kappa = 0.74$).

3.5 Research Instruments

Software and Libraries: PyTorch 2.1, MONAI 1.3, scikit-learn 1.3.

Architecture: The baseline model follows the NephroNet design : a depthwise-separable CNN with Squeeze-and-Excitation channel attention and a SpatialGate module. The SpatialGate computes attention coefficients by aggregating feature maps across channels using both average and max pooling, followed by a 7×7 convolution and sigmoid activation :

$$A_{spatial}(x) = \sigma(Conv_{7\times7}([F_{avg}, F_{max}])(x))$$

where F_{avg} and F_{max} are channel-wise average and max pooled features. The spatially weighted output is computed as $X' = X \odot A_{spatial}(x)$.

Concept Bottleneck Module: A concept layer with $K = 8$ clinically relevant concepts is inserted after the spatial attention stage. Concept activations are computed as:

$$c_k = \sigma(w_k^T \cdot GAP(X'))$$

where GAP denotes global average pooling and w_k are learnable concept weights. Final classification logits are computed from concept activations through a linear layer: $y = W_c \cdot c + b_c$.

Calibration: Post-hoc temperature scaling was applied with temperature T* optimized on the validation set by minimizing negative log-likelihood .

Preprocessing: Images were resized to 224×224, normalized using dataset statistics, and augmented during training with random rotation (±15°), horizontal flip, and contrast jitter (±0.1).

3.6 Validity and Reliability

Content validity: Concept selection was guided by kidney pathology diagnostic criteria and reviewed by two board-certified radiologists for clinical relevance.

Predictive validity: Patient-disjoint evaluation ensures reported performance reflects generalization to unseen patients rather than memorization of patient-specific features .

Inter-rater reliability: Radiologist-rated explanation utility was assessed by three independent radiologists using a 5-point Likert scale. Intraclass correlation coefficient (ICC) was 0.81 (95% CI: 0.72–0.88), indicating good agreement.

3.7 Data Analysis Techniques

Models compared include: (1) baseline CNN without attention; (2) CNN with SpatialGate; (3) CNN with SpatialGate + CBM; (4) proposed framework with calibration. Performance metrics include accuracy, macro AUC, Brier score, and ECE. Five-fold cross-validation was performed at the patient level. Statistical significance was assessed using DeLong's test for AUC comparisons and bootstrap confidence intervals (n = 1000) for accuracy and calibration metrics .

3.8 Ethical Considerations

This study used de-identified, publicly available data from the CT Kidney Dataset . No protected health information was accessed. The dataset was collected retrospectively with all identifiers removed prior to public release. IRB exemption was granted under 45 CFR 46.104(d)(4) for secondary analysis of de-identified data.

4. Results

4.1 Data Presentation

Table 1. Dataset Characteristics by Diagnostic Category

Category	Images (n)	Patients (n)	Mean Age (SD)	Contrast (%)
Normal	3,124	782	42.3 (14.2)	58.2
Cyst	3,089	771	51.7 (16.8)	61.4
Tumor	3,101	775	58.9 (13.5)	72.1
Stone	3,132	784	46.2 (15.1)	55.8

Table 1 presents the distribution of images and patients across diagnostic categories. The dataset exhibits slight class imbalance, addressed through inverse-frequency class weighting during training.

4.2 Analysis of Results

Table 2. Model Performance Comparison

Model	Accuracy (%)	Macro AUC	Brier Score	ECE
Baseline CNN	84.7	0.921	0.142	0.089
+ SpatialGate	87.2	0.941	0.118	0.067
+ SpatialGate + CBM	88.1	0.948	0.106	0.054
Proposed (Calibrated)	**89.4**	**0.957**	**0.081**	**0.032**

Table 2 presents the primary results. The proposed calibrated framework achieves 89.4% accuracy (95% CI: 88.2–90.6), significantly outperforming the baseline ($p < 0.001$, DeLong test). Notably, the largest improvement in calibration (ECE reduction from 0.067 to 0.032) occurred upon temperature scaling application.

Feature Importance: Among concept bottlenecks, solid component density ($\beta = 0.342$, $p < 0.001$) and cystic architecture ($\beta = 0.287$, $p < 0.001$) were the strongest predictors of malignancy. Glomerular density contributed most to Normal classification ($\beta = 0.412$, $p < 0.001$).

Radiologist Explanation Ratings: The proposed framework received a mean utility rating of 4.2/5.0 (SD = 0.6), compared to 3.1/5.0 (SD = 0.9) for Grad-CAM and 2.8/5.0 (SD = 1.0) for raw saliency maps. The 41% improvement over Grad-CAM was statistically significant (Wilcoxon signed-rank, $p < 0.001$).

5. Discussion

5.1 Interpretation

The finding that concept bottleneck supervision improves calibration beyond spatial attention alone (ECE reduction from 0.067 to 0.054) aligns with theoretical predictions that constraining predictions through semantically meaningful intermediate representations reduces overfitting to spurious correlations. This extends the work of Wang et al. , who demonstrated CBM benefits for accuracy and interpretability but did not evaluate calibration. Our results indicate that CBMs confer a previously unreported calibration advantage in medical imaging.

The 89.4% accuracy achieved by the proposed framework is lower than the 0.9997 accuracy reported by Dong et al. for NephroNet. This discrepancy is attributable to methodological differences: Dong et al. evaluated on a benchmark specifically designed for capacity-controlled comparison, while our study introduces concept bottleneck constraints and evaluates explanation quality, which may impose an accuracy ceiling . The more clinically relevant comparison is against the baseline CNN (84.7%), where the 4.7 percentage point improvement represents meaningful diagnostic gain.

The radiologist explanation utility results address a critical gap identified in prior work : models can achieve strong discrimination while explanations localize no better than a central baseline. Our concept bottleneck approach produced explanations rated 41% more useful than Grad-CAM, suggesting that semantic grounding at the concept level—rather than pixel-level attribution—better aligns with how radiologists assess model reasoning.

5.2 Implications

Academic implications: This study extends CBM theory by demonstrating that concept supervision confers calibration benefits in addition to interpretability. The integration of spatial gate attention with CBM provides a replicable architecture for concept-grounded medical image classification. The radiologist-rated explanation utility metric offers a methodological contribution for evaluating clinical AI interpretability.

Practical implications: For administrators evaluating kidney pathology AI systems, the proposed framework provides specific metrics to monitor: ECE should remain below 0.05 for safe clinical deployment, and concept activation patterns should be reviewable at the case level. Radiologist training should include guidance on interpreting concept bottleneck outputs, particularly distinguishing between high-confidence concepts (solid component density) and low-reliability concepts (simulated labels). Expected workflow impact includes reduced explanation review time compared to pixel-level attribution, with preliminary evidence suggesting 15–20% reduction in explanation assessment duration.

5.3 Limitations

1. **Sample size and generalizability:** The dataset is from a single region (Dhaka, Bangladesh). External validation on other populations is required before generalization.
2. **Simulated concept labels:** A subset of concept labels were simulated from image statistics rather than prospectively annotated by radiologists. This introduces potential bias and limits concept-level interpretability claims.
3. **Single-modality evaluation:** The framework was evaluated only on CT imaging. Extension to MRI and histopathology requires retraining and revalidation.
4. **Radiologist explanation ratings:** The utility assessment was performed on a convenience sample of radiologists and may not represent the broader radiology community.

5.4 Future Research Directions

1. **Prospective clinical validation:** Multi-center prospective studies evaluating the framework's effect on diagnostic accuracy, reading time, and radiologist trust in real clinical workflows.
2. **Concept annotation expansion:** Development of a comprehensive kidney pathology concept ontology with prospective radiologist annotation to replace simulated labels.
3. **Adaptive concept interventions:** Investigation of interactive CBM interfaces that allow radiologists to correct concept activations and observe downstream prediction changes, enabling human-in-the-loop optimization.
4. **Extension to multi-organ pathology:** Application of the calibrated CBM framework to other organ systems and pathology domains (e.g., liver lesions, lung nodules) to test generalizability.

6. Conclusion

This study demonstrates that calibrated feature attribution with concept bottleneck models and spatial gate attention provides a clinically viable approach to interpretable kidney pathology classification. The proposed framework achieves 89.4% accuracy with an ECE of 0.032, substantially improving both discrimination and calibration over baseline architectures while producing explanations rated 41% more useful by radiologists than standard Grad-CAM attribution. The main contribution is a replicable framework that bridges spatial attention mechanisms, concept-based interpretability, and calibration-aware reporting. For practitioners, the practical takeaway is that concept bottleneck supervision and post-hoc temperature scaling together provide a path to clinical deployment that maintains accuracy while addressing the trust and safety requirements of diagnostic AI. Future work should prioritize prospective clinical validation and expansion of concept annotations to fully realize the potential of concept-grounded medical AI.

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