
Multimodal CT Predicts AKI Risk in Pneumonia Sepsis



Sepsis frequently results in acute kidney injury, prolonging hospital stay and increasing mortality risk. Incidence estimates range from 35–50% in sepsis and rise to 50–70% in intensive care. Early prediction remains difficult because current approaches rely on blood and urine tests that can be costly, variable and not always available in time for intervention. Pneumonia is the most common source of sepsis, and chest imaging may capture disease activity relevant to systemic deterioration. A multicentre retrospective investigation developed a multimodal deep learning framework that integrates chest CT features from the lung, epicardial adipose tissue and subcutaneous adipose tissue at the T4 level with clinical and laboratory data to predict the occurrence of pneumonia sepsis-associated acute kidney injury (pSA-AKI) and its timing.

Two-Stage Model Integrating Lung and Adipose CT

The framework, termed Multimodal Cross-Attention Network (MCA-Net), was designed to fuse region-specific CT features across anatomically distinct compartments implicated in systemic inflammation. The dataset comprised 399 patients with pneumonia-associated sepsis admitted between January 2020 and July 2024 at two tertiary centres. Inclusion required non-contrast chest CT and laboratory testing on the admission day with pneumonia as the primary infection and sepsis meeting Sepsis-3 criteria. Patients with chronic kidney disease, pre-sepsis AKI, dialysis history, kidney transplantation or more than 5% missing data were excluded. AKI was defined by KDIGO criteria. Temporal categorisation followed Acute Disease Quality Initiative guidance, distinguishing early events within 48 hours of sepsis diagnosis and late events from 48 hours to 7 days.

CT acquisition used a standardised protocol. Lung and T4 vertebral landmarks were segmented with TotalSegmentator, then two radiologists manually delineated epicardial and T4-level subcutaneous fat using standard fat attenuation thresholds. In stage one, axial CT slices from lung, epicardial adipose tissue (EAT) and T4-level subcutaneous adipose tissue (T4SAT) were processed with a ResNet-18 encoder to extract region-wise features, then classified with a modified ResNet-101. In stage two, MCA-Net fused region features via a multiscale feature attention module that computed cross-regional similarity, reweighted features with attention and concatenated them for final classification using a deeper ResNet-101 head. Model development used a training and validation split from one centre, with the second centre held out as an external test set to assess generalisability. Performance was measured by accuracy, sensitivity, specificity, F1-score and area under the ROC curve.

Must Read: [Evaluating Digital Sepsis Screening Tools Across NHS Trusts](#)

Predictive Performance and Contribution of Image Modalities

Across seven evaluated input configurations, the three-region fusion model incorporating lung, T4SAT and EAT achieved the best external performance for pSA-AKI prediction. On the independent test set it reached an accuracy of 0.981 with an AUC of 0.99, and precision, recall and F1-score each at 0.9773. Dual-region models performed less well, with lung plus EAT providing the strongest two-region result and lung plus T4SAT or T4SAT plus EAT showing further reductions. Single-region models had the lowest accuracy, underscoring the value of integrating pulmonary and adipose information rather than relying on any solitary compartment.

The analysis also examined timing of AKI onset using radiomic features, clinical variables and laboratory indicators with conventional machine learning methods. Among these, LightGBM delivered the highest accuracy at 0.8409 for early versus late occurrence. Building on this, a multimodal timing model that combined deep features from the fused CT network with radiomics, clinical and laboratory data improved performance substantially on the external test set, achieving an accuracy of 0.9773, precision of 1.0000, recall of 0.9667, F1-score of 0.9829 and an AUC of 0.9612.

Baseline comparisons by AKI status identified significant differences across several routinely collected parameters. The AKI-positive group

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showed higher white cell counts, neutrophil percentage, prothrombin time and C-reactive protein, with lower albumin and differences in urine microscopy and protein grading. Blood urea nitrogen and arterial oxygenation also differed. These findings align with the framework's design that integrates clinical context with imaging features, but the core classification gains were attributed to multimodal image fusion where lung disease burden and adipose characteristics together provided discriminative information beyond single-region inputs.

Interpretability, Clinical Correlates and Temporal Signals

Model interpretability used Grad-CAM to visualise decision focus within each anatomical region. Attention maps highlighted lung parenchyma and adipose compartments, indicating that MCA-Net concentrated on disease-relevant structures rather than artefactual signals. Correlation heatmaps linked deep features from lung and EAT to platelet count, pH, D-dimer, blood urea nitrogen and urinary indicators, while T4SAT features correlated with hypertension, pH, albumin and neutrophil percentage. These associations suggest that learned imaging patterns align with physiological and laboratory markers of systemic inflammation, coagulation and renal involvement captured at admission.

For timing classification, SHAP analysis of the LightGBM model clarified how variables contributed across early and late windows. Early prediction within 48 hours was influenced by sodium, neutrophil percentage, lymphocyte count and lung or EAT radiomics. Late prediction from 48 hours to 7 days emphasised oxygenation measures, persistent electrolyte variables, age and radiomics from lung, EAT and T4SAT. Together these interpretability outputs support a biological rationale in which pulmonary inflammation and adipose tissue characteristics relate to systemic trajectories that culminate in renal injury, with distinct signals associated with early versus later onset.

The investigation reports training safeguards to reduce overfitting, including early stopping, dropout and weight decay, with an external test set kept independent of model development. The multicentre design, region-specific processing, cross-attention fusion and explicit interpretability steps strengthen confidence that performance reflects transferable signal rather than site-specific artefacts.

A two-stage multimodal deep learning approach that fuses chest CT features from lung, epicardial adipose tissue and subcutaneous fat at T4 improved prediction of acute kidney injury in pneumonia-associated sepsis and supported estimation of onset timing. The three-region model outperformed single- or dual-region inputs on an external cohort, and integration of deep features with radiomics, clinical and laboratory data further enhanced timing prediction. Attention mapping and correlation analyses indicated that image-derived features align with recognised clinical markers, offering a tractable path to interpretation. The findings highlight the clinical relevance of combining pulmonary and adipose imaging with routine data to support early risk stratification and inform monitoring and management in patients with pneumonia-related sepsis.

Source: [Academic Radiology](#)

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