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Letter to the Editor

Comment on "Chronic liver disease detection using deep convolutional neural networks with MRI data: a deep learning approach". Pol J Radiol 2026; 91: e1-e10

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Dear Editor,

We read with great interest the study by Zoroğlu Altınkaya *et al.* [1], which investigates the potential of deep convolutional neural networks in identifying chronic liver disease from magnetic resonance imaging without manual segmentation. The authors are to be commended for implementing a practical classification pipeline using raw axial and coronal sequences, and for demonstrating the feasibility of segmentation-free diagnostics in routine liver imaging. The integration of gradient-weighted class activation mapping for model explainability further enhances the translational relevance of the proposed framework. However, several methodological and clinical implications require closer examination.

The decision to train the model on image-level inputs without incorporating clinical metadata may restrict its generalisability in real-world diagnostic pathways. Chronic liver disease diagnosis typically involves an interplay of imaging, biochemical, and histopathologic data [2]. The absence of relevant clinical covariates such as serum aminotransferase levels, fibrosis scores, or comorbidity indices could inadvertently amplify imaging-derived bias and diminish the model's capacity to distinguish mimicking entities such as hepatic steatosis or congenital vascular anomalies. Without multimodal anchoring, there is a risk that high imaging accuracy may not translate to equally high diagnostic utility in diverse patient populations.

Furthermore, while the inclusion of both axial and coronal planes is a notable strength, the study does not stratify model performance by sequence type or image orientation. Given that convolutional neural networks rely on spatial hierarchies [3], variations in liver orientation across coronal and axial acquisitions may introduce latent heterogeneity in feature representation. A per-sequence or per-plane analysis would have clarified whether diagnostic gains are attributable to multi-view redundancy or to specific anatomical cues best captured in one plane. This has clinical relevance in streamlining protocols, especially in settings where limited-sequence magnetic resonance imaging is employed.

From a model optimisation perspective, the exclusive use of traditional convolutional neural networks may limit future scalability. While the authors report strong performance metrics, the model architecture appears constrained by fixed receptive fields and lacks adaptive attention mechanisms. The application of transformer-based vision models or attention-guided convolutional structures could improve interpretability and precision by prioritising clinically relevant regions [4]. Moreover, the absence of uncertainty quantification restricts insight into how the model handles borderline or ambiguous cases, which are common in early-stage liver disease.

We commend the authors for developing a robust, segmentation-independent tool that achieves 93% accuracy and a 0.939 F1 score in differentiating chronic liver disease using magnetic resonance imaging. This work represents an important step toward reducing preprocessing burden and enabling broader clinical adoption of artificial intelligence in hepatology. Future studies should consider

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Authors' contribution:
A Study design · **B** Data collection · **C** Statistical analysis · **D** Data interpretation · **E** Manuscript preparation · **F** Literature search · **G** Funds collection

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embedding clinical context, comparing performance across imaging planes, and integrating attention-based architectures to refine model adaptability and expand applicability in longitudinal care settings.

Disclosures

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4. Conflicts of interest: None.

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