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EDITED AND REVIEWED BY

Alessandro Piva,
University of Florence, Italy

*CORRESPONDENCE

Simone Bonechi
✉ bonechi@diism.unisi.it
Sandeep Kumar Mishra
✉ sandeep.kumar@yale.edu

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Editorial: Deep learning for medical imaging applications

Simone Bonechi^{1*}, Monica Bianchini¹, Paolo Andreini¹ and
Sandeep Kumar Mishra^{2,3,4*}

¹Department of Information Engineering and Mathematics, University of Siena, Siena, Italy.

²Department of Radiology and Biomedical Imaging, Yale University, New Haven, CT, United States,

³Yale Biomedical Imaging Institute, Yale University, New Haven, CT, United States, ⁴Magnetic Resonance Research Center, Yale University, New Haven, CT, United States

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Editorial on the Research Topic Deep learning for medical imaging applications

There is substantial scientific interest in leveraging artificial intelligence (AI), particularly deep learning (DL), for radiological imaging, as these methods are driving significant advancements in disease detection, diagnostic accuracy, and treatment planning (Rubin, 2019). Over the past decade, annual publications on AI in radiology have surged seven-fold, with MRI and CT dominating the field of data acquisition techniques and neuroradiology leading in contributions, followed by musculoskeletal, cardiovascular, breast, urogenital, thoracic, and abdominal subspecialties (Pesapane et al., 2018). AI has evolved into numerous practical tools with significant clinical impact. Modern systems largely depend on artificial neural networks (ANNs) inspired by brain circuitry, including Convolutional Neural Networks (CNNs), recurrent models, and newer transformer architectures. These approaches achieve high performance across MRI, CT, PET, and ultrasound data, uncovering subtle diagnostic features beyond human perception and supporting earlier disease detection and more efficient clinical workflows (Perez-Lopez et al., 2024). As datasets grow and computational frameworks mature, DL continues to reshape the future of precision medicine. Ongoing challenges include model interpretability, generalizability, and unbiased clinical deployment, but the field is rapidly progressing toward robust, trustworthy, and clinically integrated AI systems (Yang et al., 2024). Despite strong research potential on AI, its real-world clinical deployment remains limited, as effective integration into healthcare requires coordinated efforts among stakeholders and careful resolution of ethical challenges (Yang et al., 2024; Saw and Ng, 2022).

Gabriel et al. explored the critical challenge of integrating AI into patient monitoring to support continuous, real-time clinical assessment. Developed by LookDeep Health, the system showed strong performance in object detection and patient-role classification. Their study demonstrated the feasibility of computer vision as a core technology for passive, uninterrupted patient monitoring within operational hospital environments. Performance evaluation showed high accuracy in both object detection and patient-role classification. Using this platform, the investigators compiled a substantial dataset comprising computer-vision, derived predictions from more than 300 high-risk fall patients, totaling over 1,000 monitored patient-days.

Abulajiang et al. explored important insights into the association between age at menopause and the risk of major gynecologic malignancies, including cervical, ovarian, and uterine cancers. Using restricted cubic spline (RCS) regression models, the study rigorously characterized non-linear relationships between menopausal age and subsequent cancer risk. The findings suggest that menopausal age may serve as a meaningful clinical indicator, with potential value in refining individualized cancer risk assessment and informing personalized screening strategies.

Chen, Han et al. conducted a systematic review and meta-analysis evaluating the prognostic significance of growth pattern-based grading in mucinous ovarian carcinoma (MOC). The analysis indicates that expansile MOC is associated with more favorable outcomes, whereas infiltrative MOC correlates with advanced disease and poorer prognosis. The findings further underscore the importance of complete surgical staging for infiltrative MOC, while suggesting that comprehensive staging may be optional in patients with early stage expansile MOC.

Li, Ding et al. investigated radiomic features derived from ultrasound imaging and developed an externally validated predictive model integrating clinical variables with ultrasound-based radiomics to assess residual tumor status in patients with advanced epithelial ovarian cancer. The combined model demonstrated superior performance in preoperatively identifying patients likely to achieve complete resection of all visible disease and exhibited stronger generalizability compared with models based solely on clinical or radiomic features.

Yang et al. presented a comprehensive review of recent advances in the application of AI for the early screening and diagnosis of thyroid diseases. The authors summarized progress across multiple domains, including thyroid pathology and ultrasound-based assessment, and highlight emerging trends in AI-driven clinical decision support. The review further emphasized the potential of integrated AI frameworks that combine ultrasound imaging with clinical data to improve diagnostic accuracy for thyroid cancer and to enable more precise prediction of postoperative survival outcomes.

Chen, Liu et al. introduced a novel multi-class brain tumor classification model, EnSLDe, designed to capture both short-range and long-range dependencies in neuroimaging data. The architecture comprised three key components: a Feature Extraction Module (FExM), a Feature Enhancement Module (FEnM), and a Classification Module. Evaluation on two publicly available datasets demonstrated excellent performance, underscoring the model's ability to effectively integrate multi-scale feature dependencies and thereby enhance brain tumor classification accuracy.

Ma et al. validated a DL signature for non-invasive prediction of spread through air spaces (STAS) in clinical stage I lung adenocarcinoma and compared its performance with a conventional clinical-semantic model. The Swin Transformer-based signature demonstrated superior predictive accuracy, outperforming traditional approaches. This end-to-end DL framework shows strong potential as a reliable tool for estimating STAS preoperatively, providing valuable guidance for surgical planning and supporting more informed decisions regarding adjuvant therapy selection in early-stage disease.

Han et al. developed a radiomics nomogram integrating chest CT features with the ILD-GAP index to improve clinical management of rheumatoid arthritis-associated interstitial lung disease (RA-ILD). CT scans were retrospectively analyzed and staged using ILD-GAP. The model demonstrated strong accuracy in identifying low-risk RA-ILD patients. These findings suggest that this non-invasive, quantitative tool may enhance clinical decision-making by enabling more precise risk stratification and supporting individualized management strategies for RA-ILD. This integrated approach offers added clinical value for patient care.

VanBerlo et al. investigated a self-supervised learning (SSL) approach to address the scarcity of labeled data in medical imaging by leveraging representations learned from unlabeled images. Their findings showed that constructing positive pairs from nearby frames within the same video improves performance compared with pairs derived from the same image, although optimal IVPP hyperparameters vary across downstream tasks. Notably, SimCLR consistently achieved top performance for key B-mode and M-mode lung ultrasound tasks, suggesting that contrastive learning may be better suited than non-contrastive methods for ultrasound imaging applications.

Saavedra et al. developed a novel two-step DL framework to automate the assessment of supraspinatus fatty infiltration in shoulder MRIs. Their method sequentially employs a U-Net architecture to segment the muscle's region of interest, followed by a VGG-19 network to perform binary classification based on Goutallier's scale. Utilizing transfer learning on a dataset of 606 T2-weighted images, the study reported robust performance, achieving a segmentation Dice score of 0.94 and a classification AUROC of 0.99. This approach demonstrates the feasibility of fully automating the diagnostic workflow, significantly reducing the reliance on time-consuming manual segmentation by radiologists.

Li, Chen et al. proposed UnetTransCNN, a hybrid architecture designed for 3D medical image segmentation that effectively integrates CNNs with Transformers. Addressing the limitations of prior sequential fusion models, UnetTransCNN employs a parallel design where a CNN-based module captures local details while a Transformer-based module, enhanced with an Adaptive Fourier Neural Operator, captures global contextual dependencies. The model utilizes adaptive global-local coupling units to dynamically fuse features across multiple scales. Validated on the BTCV and MSD datasets, UnetTransCNN demonstrated state-of-the-art performance, significantly outperforming existing hybrid baselines like TransUNet and CoTr in segmenting both large and small anatomical structures.

Rabah et al. introduced a Vision Transformer (ViT) framework for automated detection of diabetic peripheral neuropathy (DPN) using corneal confocal microscopy (CCM) images. To address the subjectivity and labor-intensive nature of manual assessment, they developed a streamlined ViT model that classifies images as healthy or DPN without requiring pixel-level segmentation. Using a dataset of 692 images, the model achieved state-of-the-art performance (AUC 0.99; F1-score 95%), outperforming CNNs such as ResNet50. Grad-CAM-based interpretability confirmed that the model accurately focused on corneal nerve fiber loss as the key discriminative feature.

Luo et al. introduced a DL-driven data-enhancement framework that sharpens the classification of endometrial lesions in ultrasound imaging. Drawing on 1,875 images from 734 patients across six hospitals, the team couples feature-space anomaly detection for image-quality cleaning with a clustering-based soften-label strategy. After benchmarking multiple CNNs and Vision Transformers, they assembled an ensemble of ResNet50, DenseNet169, DenseNet201, and ViT-B. This model delivers 0.809 accuracy and a 0.911 macro-AUC, markedly outperforming baseline CNNs and demonstrating how targeted data curation can meaningfully elevate diagnostic performance.

Liu et al. investigated the impact of AI-guided MRI instance segmentation on laparoscopic myomectomy, with particular focus on broad-ligament fibroids, which are challenging due to their proximity to critical pelvic anatomy. The DL model segmented fibroids, uterine wall, and uterine cavity on preoperative MRI. In a randomized cohort of 120 patients, AI assistance significantly reduced operative time (118 vs. 140 min), intraoperative blood loss (50 vs. 85 mL), and improved early postoperative recovery. The authors conclude that millimeter-level anatomical mapping can substantially enhance surgical precision in complex gynecologic procedures.

Xiong et al. explored the anticancer actions of 6-gingerol in SKOV3 ovarian carcinoma cells, revealing a targeted apoptotic mechanism. The compound suppressed clonogenic growth and triggers caspase-dependent apoptosis while selectively downregulating the transcription factor Gli3, independent of Bcl-2 family alterations. Notably, 6-gingerol robustly elevated miR-506, typically diminished in ovarian tumors and miR-506 overexpression itself reduces Gli3 and promotes apoptosis. Blocking miR-506 reversed these effects, supporting a model in which 6-gingerol activated a miR-506/Gli3 axis, highlighting its therapeutic promise.

Xie et al. conducted a systematic literature review, spanning the last decade, on the application of machine learning (ML) and DL techniques to psoriasis image analysis. Fifty-three articles were retrieved from major publication repositories (WoS, PubMed, and IEEE Xplore) addressing the problems of lesion localization, lesion recognition, and severity assessment. The authors evaluated commonly used public datasets, summarized prevailing ML/DL architectures and their limitations, and identified persistent challenges, including dataset heterogeneity and limited interpretability. They also outlined emerging trends and proposed future research directions to advance automated psoriasis assessment.

Chen, Shang et al. presented a case study of a patient with recurrent low-grade endometrial stromal sarcoma (LGESS) who refused standard surgery or ablative treatment. After discontinuing chemotherapy due to impaired liver function, the patient was administered high-intensity focused ultrasound (HIFU) together with chemotherapy, which resulted in a significant reduction in tumor volume, inhibition of its progression, and restoration of liver function. This result suggests that HIFU-based combination

therapy may represent a valid option for metastatic LGESS or for patients unsuitable for surgery, particularly when integrated with real-time monitoring and precise post-treatment assessment.

Overall, this compilation demonstrates the researchers collectively push forward the development of advanced deep-learning models, reflecting their strong commitment to improving accuracy, reliability, and impact in medical imaging applications.

Author contributions

SB: Writing – original draft, Writing – review & editing. MB: Writing – original draft, Writing – review & editing. PA: Writing – original draft, Writing – review & editing. SKM: Writing – original draft, Writing – review & editing.

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