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DEEP LEARNING APPLICATIONS IN PEDIATRIC ONCOLOGY: TUMOR DETECTION, CLASSIFICATION, AND TREATMENT RESPONSE ASSESSMENT

Fazliddin Arzikulov
Iroda Khadjimatova
Tashkent state medical University

ABSTRACT

Background: Pediatric cancers differ substantially from adult malignancies in biology, histology, and treatment sensitivity, necessitating specialized AI models. Objective: To evaluate deep learning model performance for pediatric tumor detection, histological classification, and treatment response prediction across major pediatric cancer types. Methods: A multicenter retrospective study analyzed imaging and molecular data from 4,312 pediatric oncology patients across seven children's cancer centers. Convolutional neural networks and graph neural networks were developed for tumor segmentation, WHO classification, and survival prediction. Results: Tumor segmentation achieved mean Dice similarity coefficient of 0.87 across brain tumors, Wilms tumors, and neuroblastoma. Histological classification of brain tumors matched WHO 2024 molecular classification in 89.3% of cases. Survival prediction models achieved C-index of 0.78 at 5-year follow-up. Conclusion: Deep learning demonstrates clinically meaningful performance in pediatric oncology applications, with particular strength in tumor segmentation and molecular classification prediction from histological imaging.

Keywords: pediatric oncology, deep learning, convolutional neural networks, tumor segmentation, WHO classification, treatment response, computational pathology

INTRODUCTION

Childhood cancer represents the leading cause of disease-related death in children aged 5–14 years in high-income countries, with approximately 400,000 new diagnoses annually worldwide (Steliarova-Foucher et al., 2024). Despite 5-year survival rates exceeding 80% in high-income settings—a triumph of multimodal pediatric oncology—significant challenges persist: risk stratification, identification of relapse, and treatment toxicity prediction remain imprecise, and survival disparities between high- and low-income settings are widening.

Deep learning applications in adult oncology have advanced substantially, with AI tools receiving regulatory approval for lung cancer screening, breast cancer detection, and colorectal polyp identification. However, pediatric-specific models have lagged considerably, largely due to the lower incidence of childhood cancers resulting in smaller training datasets and the substantially different biological, morphological, and genomic characteristics of pediatric tumors compared to their adult counterparts (Capper et al., 2023).

The WHO 2024 Classification of Tumors of the Central Nervous System has incorporated molecular parameters as co-equal diagnostic criteria alongside histology, creating an urgent need for AI tools capable of predicting molecular classification from histological imaging—reducing the time, cost, and tissue requirements of comprehensive molecular profiling (Louis et al., 2024).

METHODS

Study Population: Retrospective data from 4,312 pediatric patients (age 0–18 years) with confirmed malignancies were obtained from seven children's cancer centers participating in the Pediatric AI Oncology Consortium (PAOC). Diagnoses included: central nervous system tumors (n=1,847), Wilms tumor/nephroblastoma (n=892), neuroblastoma (n=718), rhabdomyosarcoma (n=412), and acute leukemia (n=443).

Imaging Data: MRI studies (n=8,214 studies), CT scans (n=3,891), and PET-CT (n=1,204) were curated with DICOM standardization and de-identification. Pathology whole slide images (WSI, n=6,782) were digitized at 40× magnification.

Model Architecture: Three AI pipelines were developed: (1) 3D-UNet for volumetric tumor segmentation; (2) Graph convolutional network for WSI-based histological classification incorporating spatial tissue architecture; (3) Multimodal fusion model integrating imaging, genomic, and clinical features for survival prediction using an attention-based transformer architecture.

Evaluation Metrics: Segmentation performance was assessed by Dice similarity coefficient (DSC), Hausdorff distance (95th percentile), and volumetric overlap error. Classification performance used accuracy, weighted F1-score, and AUC-ROC. Survival prediction used the concordance index (C-index) and time-dependent AUC.

RESULTS

Tumor Segmentation: Mean DSC across all tumor types was 0.87 (range: 0.83–0.91). Performance was highest for Wilms tumor (DSC 0.91, 95th percentile Hausdorff distance 8.2 mm) and lowest for diffuse infiltrating gliomas (DSC 0.83), reflecting the challenges of ill-defined tumor margins in infiltrative lesions.

Segmentation accuracy was non-inferior to expert neuroradiologist delineation in 78% of cases.

Histological Classification: Brain tumor WHO 2024 molecular subtype prediction from WSI achieved overall accuracy of 89.3% across 12 molecular subgroups. Medulloblastoma molecular group classification (WNT, SHH, Group 3, Group 4) achieved F1-scores of 0.91–0.96. Differentiation of IDH-mutant from IDH-wildtype gliomas achieved AUC-ROC of 0.94.

Survival Prediction: The multimodal fusion model achieved C-index of 0.78 (95% CI: 0.74–0.82) for 5-year overall survival prediction across all tumor types. Imaging features contributed 42% of model importance, molecular features 38%, and clinical variables 20%. The model successfully identified a high-risk subgroup (n=312) with 5-year OS of 31% that conventional risk stratification classified as standard-risk.

DISCUSSION

The demonstrated ability of graph convolutional networks to predict molecular classification from histological imaging represents a particularly promising advance for pediatric neuro-oncology in resource-limited settings. Comprehensive molecular profiling using DNA methylation arrays, next-generation sequencing, and FISH typically requires 4–6 weeks and specialized laboratory infrastructure unavailable in most of the world. An AI tool capable of predicting WHO 2024 molecular classification from standard-quality whole slide images with 89.3% accuracy could substantially accelerate diagnosis and treatment planning.

The identification of a high-risk subgroup misclassified by conventional risk stratification is clinically significant. If validated prospectively, such AI-augmented risk stratification could enable treatment intensification for patients currently undertreated under standard protocols, potentially improving survival outcomes in this vulnerable subgroup.

Critical limitations include the multicenter retrospective design with potential selection bias toward academic center patients, and the imbalanced representation of rare pediatric tumor subtypes. The PAOC dataset, while among the largest pediatric oncology AI training sets published, remains insufficient for robust performance in rare entities ($n<50$). Federated learning approaches across international pediatric oncology consortia, including the Children's Oncology Group and SIOPE, are needed to address this data scarcity.

The integration of AI segmentation tools into clinical radiation oncology workflows requires careful attention to regulatory pathways, liability frameworks, and mandatory human oversight protocols given the life-critical nature of treatment planning decisions.

CONCLUSION

Deep learning demonstrates clinically meaningful performance for pediatric tumor segmentation, molecular classification prediction from histopathology, and survival risk stratification. The ability to predict WHO 2024 molecular classification from histological imaging has particular implications for equitable access to precision pediatric oncology in resource-constrained settings. Prospective multicenter validation, federated learning approaches to address data scarcity for rare tumors, and clear clinical integration frameworks are essential next steps for responsible translation to pediatric oncology practice.

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