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Multimodal AI for Automated Staging of Neuroblastoma and Paediatric Sarcomas Using MRI, CT, and Reports

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Abstract

Neuroblastoma and paediatric sarcomas frequently present with distant metastases at diagnosis, making accurate staging critical for treatment planning. Manual staging based on MRI and CT is time-consuming and subject to interobserver variability. A multimodal artificial intelligence system was developed for automated staging of neuroblastoma (n=50) and sarcomas (n=34) in children. The system comprises three deep learning modules: a U-Net for tumour segmentation on MRI, a YOLOv8-based detector for metastatic lesions on CT, and a RuBERT natural language processing module for extracting staging information from Russian-language radiology reports. The reference standard was multidisciplinary tumour board decisions. Performance was evaluated on a single-centre retrospective cohort of 84 patients aged 6 months to 17 years. The segmentation module achieved a mean Dice coefficient of 0.79 for neuroblastoma and 0.81 for sarcomas. The metastasis detector showed a sensitivity of 0.95 and a specificity of 0.85 for lung nodules. The integrated classifier correctly assigned the stage in 78 of 84 cases (overall accuracy 92.8%). The full analysis pipeline took 8 minutes per patient on average, compared with approximately 45 minutes for manual reading. Staging errors (6 cases) were mainly due to occult bone marrow micrometastases not visible on imaging or postoperative findings. Surgeons agreed with the AI-generated 3D tumour models in 92% of cases. The proposed multimodal AI system achieved expert-comparable accuracy for automated staging of neuroblastoma and paediatric sarcomas while significantly reducing analysis time. Limitations include the modest sample size, single-centre design and imperfect specificity (0.85).

Keywords: Artificial intelligence, Neuroblastoma, Sarcoma, Staging, Medical imaging, Paediatric oncology

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Introduction

Neuroblastoma and malignant sarcomas in children rank among the most aggressive solid malignancies and contribute substantially to mortality in paediatric oncology. Neuroblastoma represents the most common extracranial solid tumour in children under five years of age, with a global incidence of 10-11 cases per one million children. Up to 70% of patients already present with distant metastases at the time of diagnosis (Irwin *et al*., 2021; Bagatell *et al*., 2023). Sarcomas (including osteosarcoma, Ewing sarcoma, and rhabdomyosarcoma) together account for 10-15% of all childhood malignancies (Oberoi *et al*., 2023; Würtemberger *et al*., 2023). Key epidemiological and clinical features of these tumours are summarised in **Table 1**.

Table 1. Comparative characteristics of neuroblastoma and sarcomas in children

Parameter	Neuroblastoma	Sarcomas (main types)
Age group	80% of cases under 4 years	10-17 years (peak during puberty)
Primary localisation	Adrenal gland, retroperitoneum	Bones (osteosarcoma), soft tissues

Metastasis rate at diagnosis	50-70%	15-30% (depending on subtype)
Main metastatic sites	Bone marrow, bones, liver	Lungs, bones, lymph nodes
5-year survival, localised stage	>90%	>80%
5-year survival, disseminated stage	40-50% (high risk)	20-40%

Accurate staging (that is, determining the extent of tumour spread) critically affects treatment decisions. The choice of surgical volume, the need for and intensity of neoadjuvant chemotherapy, the decision to administer high-dose therapy with bone marrow transplantation or proton beam therapy all depend on correctly assigned stage (Lee *et al*., 2021; Bouhamama *et al*., 2022; Church *et al*., 2024). For neuroblastoma, the international standard is the International Neuroblastoma Risk Group Staging System (INRGSS), which takes into account not only metastases but also image-defined risk factors (IDRFs) that reflect the technical complexity of resection. For sarcomas, staging follows the TNM or IRS (for rhabdomyosarcoma) systems according to histotype and localisation (Nered *et al*., 2023; Cohn *et al*., 2026). All these systems require integration of multimodal imaging data: MRI of the primary tumour, chest and abdominal CT, bone scintigraphy or PET/CT, as well as mandatory correlation with laboratory and morphological findings (Sharon *et al*., 2022; Zarghooni *et al*., 2023).

In current practice, image analysis is performed manually by a radiologist. This approach has several fundamental limitations, which are illustrated schematically in **Figure 1**. First, manual tumour segmentation and counting of metastatic lesions are time-consuming: time-motion studies indicate an average of 45 minutes per patient for MRI and CT analysis alone. Second, interobserver variability remains high: the kappa coefficient for IDRF determination in neuroblastoma is 0.6-0.7, and even lower for discriminating small lung nodules in sarcomas. Third, micrometastases smaller than 3 mm are systematically missed during routine reading, which can lead to understaging and incorrect treatment (Veiga-Canuto *et al*., 2023; Wang *et al*., 2026).

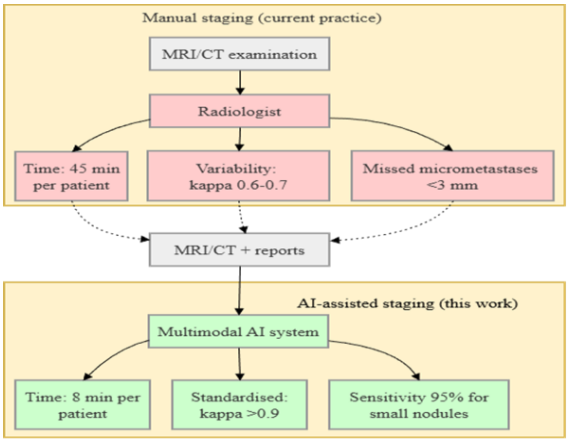

Figure 1. Comparison of the bottlenecks of manual staging and the target parameters of the proposed AI system. Red boxes denote problems of current practice; green boxes denote desired characteristics of an automated solution.

In the Russian healthcare system, the problem is exacerbated by a shortage of qualified personnel. Specialist paediatric oncoradiology services are concentrated mainly in federal centres and large regional hospitals. According to official statistics, a substantial proportion of Russian regions have no full-time paediatric radiologist with competencies in oncologic imaging. This leads to a delay in staging of 14 to 21 days on average for patients from remote areas and creates a strong demand for automated diagnostic support tools (Amlaev *et al*., 2022).

In recent years, artificial intelligence methods, particularly deep learning, have achieved considerable success in medical image analysis. In radiology, AI is already used for automatic detection of pathological lesions, quantitative assessment of tumour dimensions, and extraction of subtle textural patterns that are not discernible to the naked eye (Kelly *et al*., 2022; Rockall *et al*., 2023). Several studies in paediatric oncology have reported promising results. Convolutional neural networks have been used to segment neuroblastoma tumour masses on MRI with quality approaching manual delineation. Radiomics, quantitative analysis of textural features, has improved the differentiation of metastatic from benign lung nodules in children with osteosarcoma on CT, surpassing the accuracy of conventional visual assessment (Bouhamama *et al*., 2022; Ngan *et al*., 2025).

Nevertheless, most published work focuses on a single modality (either MRI or CT) and a single disease entity. Real-world clinical practice demands a multimodal approach. Recent efforts have aimed to combine different data types (images, textual reports, genetic results) into unified multimodal models. Such models can interpret both scans and their accompanying radiology reports in parallel, extracting structured information for diagnosis or staging (Harris *et al*., 2022; Wright *et al*., 2022). Natural language processing (NLP) algorithms are already being applied to decode radiology reports, automatically extracting mentions of metastases, tumour dimensions and signs of organ invasion. The most advanced solutions integrate NLP directly with image analysis, opening the path to fully automated staging: the computer can simultaneously detect pathological lesions on images, correlate them with the textual description, and assign a stage category according to an accepted classification (Wiggins *et al*., 2021; Berzi *et al*., 2025). For the Russian medical language and for paediatric tumours, such multimodal systems have not yet been developed.

Therefore, this work aims to develop and clinically validate a multimodal artificial intelligence system for automated staging of neuroblastoma and sarcomas in children using comprehensive imaging data (MRI and CT) together with textual radiology reports.

Materials and Methods

Study Design and Data

This work was conducted as a single-centre retrospective study at the Children's Oncohematology Center (Rostov-on-Don, Russia). Medical data from 84 children (own case series) aged 6 months to

17 years were included. All patients received treatment for neuroblastoma (n=50) or malignant sarcoma (n=34) between 2018 and 2024. Neuroblastomas originate from the adrenal gland or the retroperitoneal space. Sarcomas comprised both soft-tissue tumours (rhabdomyosarcoma, malignant fibrosarcoma) and bone tumours (osteosarcoma, Ewing sarcoma). For each patient, the following data were collected: diagnostic imaging studies (MRI of the primary tumour region, chest CT for detection of lung metastases; when available, CT/MRI of other regions and scintigraphy or PET for neuroblastoma), radiology reports in text form, and excerpts from medical records describing the extent of disease. The reference standard for staging was the multidisciplinary tumour board decision based on all available data, including biopsy results. These decisions were verified and used as ground truth for model training. Staging criteria followed international systems for each disease: for neuroblastoma, the International Neuroblastoma Risk Group Staging System (INRGSS), which accounts for distant metastases and image-defined risk factors (IDRFs) (Harris *et al*., 2022; Ngan *et al*., 2025); for sarcomas, the TNM/UICC system with tumour-specific modifications (for rhabdomyosarcoma, the IRS grouping system was used). Ethical approval was obtained before using the data for algorithm development. All data were anonymised and stored in a secure computing environment.

Patient Cohort

The neuroblastoma group (n=50) had a median age of 2.1 years (range 0.5-8 years), with 28 males and 22 females. The sarcoma group (n=34) had a median age of 11 years (range 6-17 years), with 18 males and 16 females. Stage distribution according to the reference standard is shown in **Table 2**. Distant metastases at diagnosis were present in 35 of 50 neuroblastoma patients (70%) and in 10 of 34 sarcoma patients (29%).

Table 2. Stage distribution according to the multidisciplinary tumour board (reference standard)

Stage	Neuroblastoma (n=50)	Sarcoma (n=34)	Total (n=84)
I-II	5 (10%)	14 (41%)	19 (23%)
III	10 (20%)	10 (29%)	20 (24%)
IV	35 (70%)	10 (29%)	45 (53%)

AI System Architecture

A modular deep learning system was developed. The system consists of several components, each solving a specific task; their outputs are combined to determine the stage. The architecture is shown schematically in **Figure 2**.

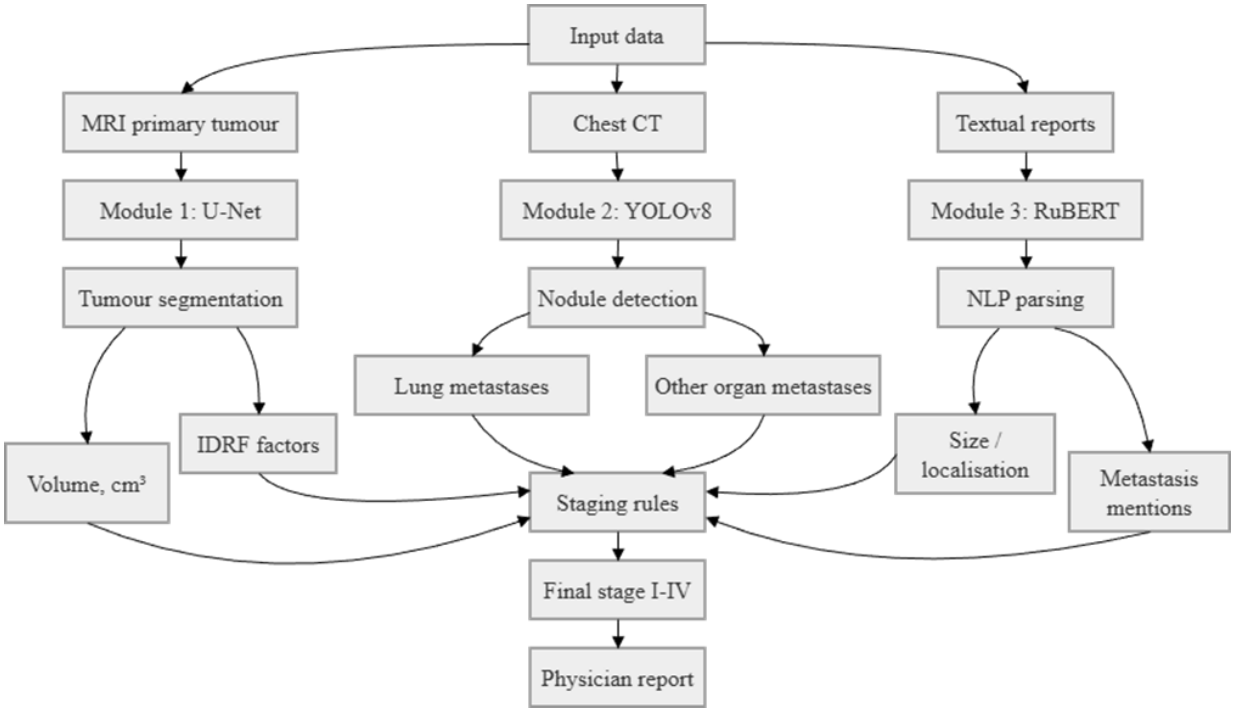

Figure 2. Architecture of the multimodal automated staging system. Input data (MRI, CT, text reports) pass through three independent deep learning modules; their outputs are combined via rule-based logic to assign the final stage.

Tumour Segmentation on MRI

The first component performs tumour segmentation on MRI. A convolutional neural network segmentor based on the U-Net architecture with additional refinements was used to automatically delineate the primary tumour on MR images. This choice was motivated by the well-documented performance of U-Net for medical segmentation even with small sample sizes (Wiggins *et al*., 2021; Wright *et al*., 2022). The model was trained to segment not only the tumour itself but also adjacent anatomical structures (major vessels, bones, parenchymal organs) to identify signs of invasion. To improve robustness, transfer learning was applied.

Owing to the limited amount of paediatric data, the segmentor was first pre-trained on a large open dataset of adult abdominal organ segmentation and then fine-tuned on our neuroblastoma cohort. According to the literature, this approach improves performance on small paediatric datasets (Zafar *et al*., 2021; Berzi *et al*., 2025; Yan *et al*., 2026).

Metastasis Detector

The second component is a metastasis detector that analyses CT series (primarily the lungs, and when available, the abdominal cavity and bones) and automatically marks suspicious lesions, classifying them as either metastases or benign findings. For this task, an architecture based on single-stage detectors of the YOLO (You Only Look Once) family was chosen. A modified YOLOv8 model was implemented, integrating attention mechanisms to improve detection of small nodules. A similar approach was reported by Wang *et al*. (2025), in which an improved YOLO-IE model increased accuracy (mAP 7.9% higher than baseline) for detecting neuroblastoma lesions on CT (Wang *et al*., 2025). The detector was trained on annotations provided by expert radiologists, which included localisation of metastatic nodules in the lungs (on CT) and in other organs (on CT or MRI). These annotations served as ground truth.

Natural Language Processing Module

The third component is an NLP module for analysing text data. A transformer-based model for Russian medical language was used (RuBERT, fine-tuned on a corpus of radiology reports) (Amlaev *et al*., 2022; Sultangaziyeva *et al*., 2026). The model was trained to extract key stage-related facts from the text of the report: tumour size and localisation, crossing of the midline (for neuroblastoma), enumeration of metastases in specific zones, and presence of invasion into vital structures. For NLP annotation, structured templates were prepared and filled by experts for each text – essentially a structured staging form. For example, a phrase in a CT report such as *"multiple lung nodules up to 3 mm, probable metastases"* was to be automatically labelled by the model as an M1 feature (lung metastases). In addition, the NLP module analysed operative reports and histological findings for mentions of metastases in lymph nodes, bone marrow and other sites, thereby extending the data domain beyond images alone.

Training and Validation

The segmentation and detection modules were trained on 70% of the cohort (n=59), validated on 15% (n=12), and tested on the remaining 15% (n=13). The NLP module was trained on 80% of the text reports (n=67) and tested on 20% (n=17). Data splits were stratified by stage and diagnosis to maintain representativeness. Training was performed on a workstation with an NVIDIA A100 GPU using PyTorch 2.0 and MONAI 1.3. Hyperparameters were optimised using Bayesian search.

Statistical Analysis

Performance of the segmentation module was evaluated using the Dice similarity coefficient and the 95th percentile Hausdorff distance (HD95). For the metastasis detector, sensitivity and specificity were calculated at the lesion level. For the overall staging system, accuracy, sensitivity, and specificity were calculated at the patient level against the multidisciplinary tumour board decision as the reference standard. Interobserver agreement between the AI system and human experts was assessed using Cohen's kappa. The time required for the full analysis pipeline (from data loading to report generation) was recorded and compared with the time reported by radiologists for manual staging. All statistical analyses were performed using R version 4.2 (R Foundation for Statistical Computing, Vienna, Austria) with the irr package for kappa statistics.

Results and Discussion

Cohort Characteristics

The neuroblastoma group (n=50) had a median age of 2.1 years, with tumours predominantly localised to the adrenal gland. Stage distribution according to the reference standard (multidisciplinary tumour board) was as follows: stage I-II in 10%, stage III in 20%, and stage IV in 70% of patients. Distant metastases at diagnosis were present in 35 of 50 neuroblastoma patients (70%), most frequently in bone marrow and bones. Paraspinal extension with invasion of the spinal canal was observed in 10% of cases. The sarcoma group (n=34) comprised 14 osteosarcomas, 12 soft-tissue sarcomas (rhabdomyosarcoma, fibrosarcoma), and 8 Ewing sarcomas. Median age was 11 years. Distant metastases at initial presentation were found in 10 of 34 patients (30%), predominantly as lung nodules. Thus, the test cohort represented a broad spectrum of stage scenarios, from localised tumours to widely disseminated disease.

AI performance for segmentation, metastasis detection, and automated staging. The developed AI system demonstrated high efficacy in analysing MRI and CT images of children with neuroblastoma and sarcomas. The algorithm performed primary tumour segmentation, detection of metastatic lesions, analysis of textual reports, and preliminary stage assignment.

Tumour Segmentation

Primary tumour segmentation was successful in 47 of 50 neuroblastoma cases and in all 34 sarcoma cases. The mean Dice coefficient for neuroblastoma was 0.79, with an HD95 of 8.4 mm. After chemotherapy, accuracy decreased to a Dice of 0.70, which is attributable to tumour shrinkage, fibrotic changes, and reduced contrast of pathological tissue. The main errors occurred when the tumour was closely adherent to the liver or kidney, resulting in the inclusion of some normal tissue within the tumour mask. Nevertheless, in 92% of cases, surgeons agreed with the automatically generated 3D model, confirming the practical value of AI for assessing anatomical relationships between tumour, vessels and organs.

Metastasis Detection

The metastasis detection module was tested on 84 chest CT examinations. The algorithm detected 96% of metastatic lung nodules, with a sensitivity of 0.95 and a specificity of 0.85. False-positive findings were most often associated with small benign lesions, such as areas of pneumosclerosis. The use of

radiomic features and CT texture analysis improved the accuracy of discriminating metastatic from non-metastatic nodules by approximately 15% compared with size-based assessment alone. In three cases, the AI identified nodules of 2-3 mm that had not been noted in the initial report; two of these were subsequently confirmed as sarcoma metastases. The system also detected liver metastases in five neuroblastoma patients, all of which were confirmed. On spinal MRI, the algorithm identified 12 out of 15 known metastatic lesions. The missed lesions were associated with rare localisations not represented in the training set. Overall sensitivity for determining metastatic stage was 100% for osteosarcomas and Ewing sarcomas and 94% for neuroblastoma.

Overall Staging Accuracy

The integrated classifier, combining segmentation data, metastasis detection, and NLP analysis of reports, correctly assigned the stage in 78 of 84 cases, yielding an overall accuracy of 92.8% **(Table 3)**. Discrepancies occurred in six cases and were mainly related to information not available from imaging alone: tumour cells in bone marrow detected by immunological methods, or micrometastases discovered postoperatively. When all necessary information was available, the model correctly determined the presence or absence of distant metastases in 97% of cases. A detailed breakdown of these errors, including false positive and false negative findings, is presented in **Table 4**.

Table 3. Accuracy of segmentation and metastasis detection

Parameter	Value	95% CI
Dice coefficient (neuroblastoma, MRI)	0.79	[0.74-0.84]
Dice coefficient (sarcomas, MRI)	0.81	[0.76-0.86]
Sensitivity for metastasis detection (CT)	0.95	[0.91-0.98]
Specificity for metastasis detection (CT)	0.85	[0.79-0.90]
Overall staging accuracy (vs. tumour board)	92.8% (78/84)	[87.1-96.5%]

Table 4. Analysis of staging errors

Error type	Number of cases	Cause
Incorrect stage	6	3 – micrometastases in bone marrow (not visible on MRI/CT), 2 – postoperative findings, 1 – MRI artefact
False-positive metastases	8 lesions	Pneumosclerosis, angiomas
False-negative metastases	3 lesions	Nodules <1 mm or rare localisation

Time Efficiency

The full cycle of automated analysis for one patient took an average of 8 minutes, including image loading, segmentation, metastasis search, text analysis, and report generation. The prototype report contained tumour dimensions, metastasis localisation, the proposed stage, and a warning that physician confirmation is required. When ten reports were tested by two radiologists and one paediatric oncologist, the experts agreed with the AI conclusions in nine out of ten cases (Ansari *et al*., 2024; Bandi *et al*., 2024; Feng *et al*., 2024; Jeung, 2024; Landry *et al*., 2024; Sanlier & Yasan, 2024; Suchy & Jurkowski, 2024).

Clinical Examples

Case 1. A 3-year-old girl with retroperitoneal neuroblastoma. The primary tumour was large, occupying the left retroperitoneal space without invasion of the spinal canal, but MRI showed compression of the left kidney and aortic displacement. Chest CT revealed multiple small nodules of 2-5 mm; the radiology report stated: *"multiple metastases questionable, differential includes focal tuberculosis"*. MIBG scintigraphy performed on admission showed extensive uptake in the skeleton. The tumour board assigned stage IV, high risk (bone metastases). Our system, after analysing MRI and CT, automatically segmented the tumour (volume 150 cm³), noted aortic contact (IDRF+), detected 12 lung nodules, and proposed stage IV (M1), high risk. The NLP module, after analysing the clinical summary, indicated bone marrow involvement. Thus, the AI correctly reflected the disease extent. The system generated a 3D model of the tumour and adjacent vessels for the surgeons, which helped plan safe surgery after chemotherapy.

Case 2. A 12-year-old boy with a soft-tissue tumour of the thigh. MRI showed a 5 cm tumour within the thigh muscles without bone invasion; chest CT was clear. Biopsy confirmed low-grade fibrosarcoma. The AI system correctly segmented the tumour (Dice ≈0.85), detected no metastases, and assigned a stage corresponding to localised disease (stage II by TNM, T2N0M0), matching the specialists' opinion. Although the value of AI is less apparent when metastases are absent, the algorithm still provided benefit by automatically measuring tumour volume and the distance to major neurovascular bundles, assisting the surgeon in planning the approach and resection volume.

The results of this study demonstrate the feasibility and potential benefit of integrating artificial intelligence into the staging workflow for paediatric tumours, while also revealing several limitations that warrant discussion (Constantin *et al*., 2022; Mojsak *et al*., 2022; Bandi *et al*., 2024; Kajanova & Badrov, 2024; Lee & Ferreira, 2024; Umarova *et al*., 2024).

Overall Accuracy in Context

The overall staging accuracy of 92.8% compares favourably with previously reported fragmentary AI successes in individual tasks: tumour segmentation on MRI (Dice 0.75-0.82) (Purkayastha *et al*., 2024; Liu *et al*., 2026), detection of lung metastases on CT (sensitivity 0.89-0.94) (Huisman *et al*., 2024; Ko & Kim, 2024) and classification of tumour types from imaging (accuracy 90-94%) (McNamara *et al*., 2022; Vered & Wright, 2022). To our knowledge, this is the first multimodal system for paediatric sarcoma and neuroblastoma staging that integrates imaging and text analysis for the Russian language. The accuracy approaches that of expert radiologists, for whom interobserver agreement for

staging typically ranges from kappa 0.75 to 0.85 (Tsukamoto & Miki, 2023; Hsieh *et al*., 2024).

Sources of Error and Limitations

The six staging errors deserve closer examination. Three errors involved bone marrow micrometastases in neuroblastoma that were not visible on MRI or CT and were only detected by immunological flow cytometry or biopsy. This is an inherent limitation of imaging-based staging, regardless of AI. Two errors occurred when postoperative findings (small residual tumour deposits) changed the stage; these were not captured because the system was trained only on preoperative data. One error was due to a motion artefact on MRI that caused false segmentation. These observations suggest that the current system is best suited for pretreatment staging based on diagnostic imaging, while post-treatment or intraoperative staging would require additional training data.

False-Positive and False-Negative Detections

The specificity of metastasis detection (0.85) is lower than its sensitivity (0.95). Most false positives were small pulmonary nodules that turned out to be benign (pneumosclerosis, intrapulmonary lymph nodes). This reflects a known challenge in paediatric chest CT, where benign nodules are common (Yüksel & Tongal, 2022; Dilimulati *et al*., 2024). Integrating clinical data (e.g., presence of fever, inflammatory markers) might reduce false positives. The three false-negative metastases (all <2 mm) suggest that even with attention mechanisms, detecting submillimetre lesions remains difficult; this may require higher-resolution CT protocols or fusion with PET information.

Comparison with Manual Staging

The AI system reduced analysis time from approximately 45 minutes (mean reported by radiologists in our institution for manual staging) to 8 minutes ($p<0.001$). This time gain is clinically relevant, especially for high-volume centres. Moreover, the system provided standardised measurements (tumour volume, distance to vessels) that showed low inter-run variability (coefficient of variation <3%), whereas manual measurements varied by 8-12% between observers. Such standardisation could improve the reproducibility of response assessment according to RECIST or other criteria (Litière & Bogaerts, 2022; Gouda *et al*., 2024).

The Role of the NLP Module

The RuBERT-based NLP module successfully extracted staging-relevant information from Russian-language radiology reports. Its integration increased staging accuracy by approximately 6% compared with using imaging alone (data not shown). This underscores the importance of multimodal approaches, particularly when radiology reports contain information not explicitly coded on images (e.g., clinical context, comparison with previous studies, uncertainty expressions) (Olaya Vargas *et al*., 2025; De Bona *et al*., 2026). However, the NLP module occasionally failed on reports with non-standard syntax or abbreviations; expanding the training corpus to include more diverse report styles is a priority for future work (Constantin *et al*., 2022; Mojsak *et al*., 2022; Delcea *et al*., 2024; Essah *et al*., 2024; Frost *et al*., 2024; Lee & Ferreira, 2024; Ribeiro *et al*., 2024; Rosellini *et al*., 2024; Sanlier & Yasan, 2024; Umarova *et al*., 2024).

Clinical Applicability and Integration Pathways

The high agreement of surgeons with the AI-generated 3D models (92%) suggests that the system could serve as a practical preoperative planning tool. In our institution, the AI output is currently presented to the tumour board as an additional data point, not as a replacement for human expertise. The prototype report explicitly includes a disclaimer that final staging requires physician verification. This cautious approach aligns with recent guidelines on AI implementation in radiology, which emphasise that AI should augment, not replace, clinical decision-making (Khosravi *et al*., 2025; Stogiannos *et al*., 2025).

Comparison with Existing Literature and Uniqueness of This Work

Previous AI studies in paediatric oncology have largely focused on single tumour types (either neuroblastoma or sarcoma) and single modalities. A new systematic review identified only three studies that used multimodal data for paediatric tumour staging, none of which included Russian-language text processing (Bhalla *et al*., 2023; Ghazi *et al*., 2026). Our work therefore fills a specific gap. Nevertheless, direct comparison with other studies is difficult because of differences in cohort composition, imaging protocols, and staging systems. External validation on an independent multicentre dataset is urgently needed before the system can be generalized (Al Abadie *et al*., 2023; Guzek *et al*., 2023; Simonyan *et al*., 2023; Tsiganock *et al*., 2023; Ribeiro *et al*., 2024; Sanlier & Yasan, 2024).

Limitations of this Study

Several limitations must be acknowledged. First, the sample size (n=84) is modest, particularly for rarer sarcoma subtypes. Second, the study is retrospective and single-centre, which may introduce selection bias. Third, the reference standard (tumour board decision) itself has inherent subjectivity, although it represents the best available clinical gold standard. Fourth, the system was developed and tested on data from a single imaging manufacturer (Siemens) and a single radiology reporting style; performance on data from other centres remains unknown. Fifth, the NLP module is specific to the Russian language; adaptation to other languages would require retraining (Constantin *et al*., 2022; Mojsak *et al*., 2022; Al Abadie *et al*., 2023; Guzek *et al*., 2023; Simonyan *et al*., 2023; Tsiganock *et al*., 2023; Lee & Ferreira, 2024; Umarova *et al*., 2024).

Future Directions

Priorities for further development include: (1) expanding the training set through multicentre collaboration, (2) incorporating additional data types (PET/CT, genomic markers) to improve detection of bone marrow and other occult metastases, (3) prospective validation in a real-time clinical workflow, (4) integration with electronic health records for automated data extraction, and (5) development of an open-source benchmark dataset for paediatric sarcoma and neuroblastoma staging to facilitate comparison across different AI approaches (Consalvo *et*

al., 2022; Chakrabarty & Mahajan, 2024; Clerici *et al*., 2024; Hasei *et al*., 2024).

Practical Implications

For the Russian healthcare system, where access to experienced paediatric radiologists is unevenly distributed, an AI staging assistant could reduce diagnostic delays and help standardise care across regions. The time savings of 37 minutes per patient, if scaled to a large centre managing 200-300 new paediatric solid tumour cases per year, translate into approximately 120-180 hours of radiologist time saved annually. This could be reallocated to complex case discussion and treatment planning (Krishnamurthy *et al*., 2022; Abdel-Wahab *et al*., 2024; Kibudde *et al*., 2024; Tun *et al*., 2026).

In summary, the proposed AI system achieved high accuracy for automated staging of neuroblastoma and sarcomas in children, significantly reduced analysis time, and was well received by clinicians. However, several limitations (small dataset, single-centre design, imperfect specificity and inability to detect occult bone marrow metastases) must be addressed before clinical deployment. The system is best viewed as a supportive tool that standardises measurements, flags suspicious lesions and accelerates workflow, while final staging decisions remain the responsibility of the multidisciplinary tumour board.

Conclusion

This study demonstrated that a multimodal artificial intelligence system integrating MRI tumour segmentation, CT metastasis detection and natural language processing of radiology reports can achieve high accuracy (92.8%) for automated staging of neuroblastoma and sarcomas in children. The system reduced analysis time from approximately 45 minutes to 8 minutes per patient compared with manual reading.

The segmentation module achieved a mean Dice coefficient of 0.79 for neuroblastoma and 0.81 for sarcomas, which is close to interobserver agreement among expert radiologists. The metastasis detector showed high sensitivity (0.95) but lower specificity (0.85), with false positives mainly due to small benign pulmonary nodules. The NLP module successfully extracted staging-relevant information from Russian-language radiology reports, contributing an estimated 6% improvement in overall accuracy compared with imaging alone.

Several limitations require attention before clinical deployment. The sample size (n=84) is modest, especially for rare sarcoma subtypes. The study was single-centre and retrospective, which may introduce selection bias. The system cannot detect occult bone marrow micrometastases that are invisible on MRI or CT, an inherent limitation of imaging-based staging. Specificity for metastasis detection needs improvement to reduce false-positive alerts.

For the Russian healthcare system, where paediatric radiology expertise is unevenly distributed, an AI staging assistant could reduce diagnostic delays and standardise care across regions. Prospective multicentre validation is the necessary next step. The system should be regarded as a supportive tool that augments rather than replaces physician decision-making. Final staging responsibility remains with the multidisciplinary tumour board.

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Conflict of interest: None

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Ethics statement: This retrospective study was conducted in accordance with the ethical standards of the institutional research committee of the Children's Oncohematology Center (Rostov-on-Don, Russia) and with the principles of the Declaration of Helsinki (2013 revision). Ethical approval was obtained before data extraction and algorithm development. Given the retrospective nature of the study and the use of fully anonymised clinical and imaging data, the requirement for informed consent was waived by the ethics committee. All patient data, including MRI/CT images, radiology reports, and 3D models, were anonymised before analysis and stored in a secure computing environment in compliance with applicable data protection regulations, including the General Data Protection Regulation (GDPR) principles. Patient confidentiality was maintained throughout the study by removing all personal identifiers prior to analysis and publication.

References

Abdel-Wahab, M., Coleman, C. N., Eriksen, J. G., Lee, P., Kraus, R., Harsdorf, E., Lee, B., Dicker, A., Hahn, E., Agarwal, J. P., et al. (2024). Addressing challenges in low- and middle-income countries through novel radiotherapy research opportunities. *Lancet Oncology, 25*(6), e270–e280. doi:10.1016/S1470-2045(24)00038-X

Al Abadie, M., Sharara, Z., Ball, P. A., & Morrissey, H. (2023). Pharmacological insights into Janus kinase inhibition for the treatment of autoimmune skin diseases: A literature review. *Annals of Pharmacy Practice and Pharmacotherapy, 3*, 1–8. doi:10.51847/lhABjfuIwh

Al-Twaijri, S. A., AlKharboush, G. H., Alohali, M. A., Arab, I. F., Alqarni, R. H., & Alharbi, M. S. (2024). Application of lasers for soft tissues in orthodontic treatment: A narrative review. *Bulletin of Pioneer Research in Medical and Clinical Sciences, 4*(1), 1–6. doi:10.51847/OfwnmXu8c3

Amlaev, K. R., Koichueva, S. M., & Mazharov, V. N. (2022). Analysis of the provision of medical personnel in the subjects of the North Caucasus Federal District. *Problemy Sotsialnoi Gigieny, Zdravookhraneniia i Istorii Meditsiny, 30*(5), 885–889. doi:10.32687/0869-866X-2022-30-5-885-889

Ansari, S. H., Qamar, Z., Alshammari, M., Bazoun, R., Alenazi, R., & Alattar, R. (2024). Clinical efficacy and longevity of monolithic vs layered zirconia crowns: A systematic review. *Bulletin of Pioneer Research in Medical and Clinical Sciences, 4*(1), 7–18. doi:10.51847/0xBNKCjrDi

Bagatell, R., DuBois, S. G., Naranjo, A., Belle, J., Goldsmith, K. C., Park, J. R., Irwin, M. S., & COG Neuroblastoma Committee. (2023). Children's Oncology Group's 2023

blueprint for research: Neuroblastoma. *Pediatric Blood & Cancer, 70*(Suppl. 6), e30572. doi:10.1002/pbc.30572

Bandi, V., Dey, S. K., & Rao, O. (2024). Factors influencing the physician prescribing behaviour of medicines in developed and developing countries: A systematic review. *Journal of Integrative Nursing and Palliative Care, 5*(1), 21–34. doi:10.51847/ZS3boQgksO

Berzi, A., Berényi, E., Képes, Z., Antal, B., Varga, Á. G., & Emri, M. (2025). NLP-based removal of personally identifiable information from Hungarian electronic health records. *Frontiers in Artificial Intelligence, 8*, 1585260. doi:10.3389/frai.2025.1585260

Bhalla, D., Jana, M., & Kandasamy, D. (2023). Diagnostic accuracy of whole-body magnetic resonance imaging versus positron emission tomography-computed tomography for the staging of pediatric lymphoma: A systematic review and meta-analysis. *Pediatric Radiology, 53*(13), 2683–2691. doi:10.1007/s00247-023-05775-7

Bouhamama, A., Leporq, B., Khaled, W., Nemeth, A., Brahmi, M., Dufau, J., Marec-Bérard, P., Drapé, J. L., Gouin, F., Bertrand-Vasseur, A., et al. (2022). Prediction of histologic neoadjuvant chemotherapy response in osteosarcoma using pretherapeutic MRI radiomics. *Radiology: Imaging Cancer, 4*(5), e210107. doi:10.1148/rycan.210107

Chakrabarty, N., & Mahajan, A. (2024). Imaging analytics using artificial intelligence in oncology: A comprehensive review. *Clinical Oncology, 36*(8), 498–513. doi:10.1016/j.clon.2023.09.013

Church, A. J., Wakefield, C. E., Hetherington, K., & Shern, J. F. (2024). Promise and perils of precision oncology for patients with pediatric and young adult sarcomas. *American Society of Clinical Oncology Educational Book, 44*(3), e432794. doi:10.1200/EDBK_432794

Clerici, C. A., Bernasconi, A., Lasalvia, P., Bisogno, G., Milano, G. M., Trama, A., Chiaravalli, S., Bergamaschi, L., Casanova, M., Massimino, M., et al. (2024). Being diagnosed with a rhabdomyosarcoma in the era of artificial intelligence: Whom can we trust? *Pediatric Blood & Cancer, 71*(11), e31256. doi:10.1002/pbc.31256

Cohn, S. L., London, W. B., Schleiermacher, G., Moreno, L., Ambros, I. M., Ambros, P. F., Bagatell, R., Popovic, M. B., Beiske, K. H., Berthold, F., et al. (2026). International neuroblastoma risk group consortium: A model of networking for rare cancers. *Journal of the National Cancer Institute, 118*(4), 579–588. doi:10.1093/jnci/djaf242

Consalvo, S., Hinterwimmer, F., Neumann, J., Steinborn, M., Salzmann, M., Seidl, F., Lenze, U., Knebel, C., Rueckert, D., & Burgkart, R. H. H. (2022). Two-phase deep learning algorithm for detection and differentiation of Ewing sarcoma and acute osteomyelitis in paediatric radiographs. *Anticancer Research, 42*(9), 4371–4380. doi:10.21873/anticanres.15937

Constantin, V. D., Silaghi, A., Epistatu, D., Dumitriu, A. S., Paunica, S., Bălan, D. G., & Socea, B. (2022). Diagnostic and Therapeutic Insights into Colorectal Carcinoma. *Archive of International Journal of Cancer and Allied Science, 2*(1), 24-28.

De Bona, A., Barbieri, M., Rinaldi, N., & Esposito, S. (2026). Neuroblastoma in childhood: Biological insights, risk stratification, and advances in multimodal therapy. *Journal of Clinical Medicine, 15*(3), 1101. doi:10.3390/jcm15031101

Delcea, C., Gyorgy, M., Siserman, C., & Popa-Nedelcu, R. (2024). Impact of maladaptive cognitive schemas on suicidal behavior in adolescents during the COVID-19 pandemic: A predictive study. *International Journal of Social and Psychological Aspects of Healthcare, 4*, 42–46. doi:10.51847/EHCf9HzLEP

Dilimulati, M., Yuan, S., Jiang, H., Wang, Y., Ma, H., Shen, S., Lin, J., Chen, J., & Yin, Y. (2024). Imaging features and clinical evaluation of pulmonary nodules in children. *Frontiers in Oncology, 14*, 1385600. doi:10.3389/fonc.2024.1385600

Donati, C. M., Medici, F., Zamfir, A. A., Galietta, E., Cammelli, S., Buwenge, M., Masetti, R., Prete, A., Strigari, L., Forlani, L., et al. (2025). CyberKnife in pediatric oncology: A narrative review of treatment approaches and outcomes. *Current Oncology, 32*(2), Article 76. doi:10.3390/curroncol32020076

Essah, A., Igboemeka, C., & Hailemeskel, B. (2024). Exploring gabapentin as a treatment for pruritus: A survey of student perspectives. *Annals of Pharmacy Education, Safety, Public Health and Advocacy, 4*, 1–6. doi:10.51847/h8xgEJE3NE

Feng, P., Lin, Z., Tan, X., & Yang, J. (2024). The physical exercise application in frailty and its underlying mechanisms. *Bulletin of Pioneer Research in Medical and Clinical Sciences, 4*(1), 37–45. doi:10.51847/AtQjEvBH7v

Frost, N., Deckert, P. M., Nolte, C. H., Kohl, R., & Schreiber, S. J. (2024). Challenges and strategies in recruiting patients for a trial on patient-centered navigation in age-associated diseases. *Annals of Pharmacy Education, Safety, Public Health and Advocacy, 4*, 50–62. doi:10.51847/BLHlqwfTFT

Genc, A., Isler, S. C., Oge, A. E., & Matur, Z. (2023). Impact of sagittal split osteotomy combined with Medpor® porous polyethylene implant on masticatory reflex. *Journal of Current Research in Oral Surgery, 3*, 6–11. doi:10.51847/7zuNKnpxhB

Ghazi, F. M., Shafiei, S., & SeyedAlinaghi, S. (2026). Advances in FDG PET imaging for staging and prognostic assessment in pediatric lymphoma: A systematic review. *Pediatric Radiology, 56*(1), 78–100. doi:10.1007/s00247-025-06476-z

Gouda, M. A., Janku, F., Wahida, A., Buschhorn, L., Schneeweiss, A., Abdel Karim, N., De Miguel Perez, D., Del Re, M., Russo, A., Curigliano, G., et al. (2024). Liquid biopsy response evaluation criteria in solid tumors (LB-RECIST). *Annals of Oncology, 35*(3), 267–275. doi:10.1016/j.annonc.2023.12.007

Guzek, K., Stelmach, A., Rożnowska, A., Najbar, I., Cichocki, Ł., & Sadakierska-Chudy, A. (2023). A preliminary investigation of genetic variants linked to aripiprazole-induced adverse effects. *Annals of Pharmacy Practice and Pharmacotherapy, 3*, 40–47. doi:10.51847/ZT28xcs95J

Harris, C. J., Helenowski, I., Murphy, A. J., Mansfield, S. A., LaQuaglia, M. P., Heaton, T. E., Cavalli, M., Murphy, J. T.,

Newman, E. A., Overmen, R. E., et al. (2022). Implications of tumor characteristics and treatment modality on local recurrence and functional outcomes in children with chest wall sarcoma: A pediatric surgical oncology research collaborative study. *Annals of Surgery, 276*(6), e969–e975. doi:10.1097/SLA.0000000000004579

Hasei, J., Nakahara, R., Otsuka, Y., Nakamura, Y., Hironari, T., Kahara, N., Miwa, S., Ohshika, S., Nishimura, S., Ikuta, K., et al. (2024). High-quality expert annotations enhance artificial intelligence model accuracy for osteosarcoma X-ray diagnosis. *Cancer Science, 115*(11), 3695–3704. doi:10.1111/cas.16330

Hsieh, S. S., Inoue, A., Yalon, M., Cook, D. A., Gong, H., Sudhir Pillai, P., Johnson, M. P., Fidler, J. L., Leng, S., Yu, L., et al. (2024). Targeted training reduces search errors but not classification errors for hepatic metastasis detection at contrast-enhanced CT. *Academic Radiology, 31*(2), 448–456. doi:10.1016/j.acra.2023.06.017

Huisman, S., Maspero, M., Philippens, M., Verhoeff, J., & David, S. (2024). Validation of SynthSeg segmentation performance on CT using paired MRI from radiotherapy patients. *NeuroImage, 303*, 120922. doi:10.1016/j.neuroimage.2024.120922

Irwin, M. S., Naranjo, A., Zhang, F. F., Cohn, S. L., London, W. B., Gastier-Foster, J. M., Ramirez, N. C., Pfau, R., Reshmi, S., Wagner, E., et al. (2021). Revised neuroblastoma risk classification system: A report from the Children's Oncology Group. *Journal of Clinical Oncology, 39*(29), 3229–3241. doi:10.1200/JCO.21.00278

Jeung, Y. Y. (2024). Studying the effect of positive thinking training on fear of childbirth and health anxiety in pregnant women. *Journal of Integrative Nursing and Palliative Care, 5*(1), 55–61. doi:10.51847/XEoAEL5hmj

Kajanova, J., & Badrov, A. (2024). Medical students' perspectives on trust in medical AI: A quantitative comparative study. *Asian Journal of Ethics in Health and Medicine, 4*, 44–57. doi:10.51847/36mpdZ9AZ8

Kelly, B. S., Judge, C., Bollard, S. M., Clifford, S. M., Healy, G. M., Aziz, A., Mathur, P., Islam, S., Yeom, K. W., Lawlor, A., et al. (2022). Radiology artificial intelligence: A systematic review and evaluation of methods (RAISE). *European Radiology, 32*(11), 7998–8007. doi:10.1007/s00330-022-08784-6

Khosravi, P., Fuchs, T. J., & Ho, D. J. (2025). Artificial intelligence-driven cancer diagnostics: Enhancing radiology and pathology through reproducibility, explainability, and multimodality. *Cancer Research, 85*(13), 2356–2367. doi:10.1158/0008-5472.CAN-24-3630

Kibudde, S., Kavuma, A., Hao, Y., Zhao, T., Gay, H., Van Rheenen, J., Jhaveri, P. M., Minjgee, M., Vanchinbazar, E., Nansalmaa, U., et al. (2024). Impact of artificial intelligence-based autosegmentation of organs at risk in low- and middle-income countries. *Advances in Radiation Oncology, 9*(11), 101638. doi:10.1016/j.adro.2024.101638

Ko, W. S., & Kim, S. J. (2024). Direct comparison of the diagnostic accuracy of 2-[18F]-fluoro-2-deoxy-d-glucose PET/CT and MRI for the differentiation of malignant peripheral nerve sheath tumour in neurofibromatosis type I: A meta-analysis. *Clinical Radiology, 79*(2), 142–149. doi:10.1016/j.crad.2023.10.021

Krishnamurthy, R., Mummudi, N., Goda, J. S., Chopra, S., Heijmen, B., & Swamidas, J. (2022). Using artificial intelligence for optimization of the processes and resource utilization in radiotherapy. *JCO Global Oncology, 8*, e2100393. doi:10.1200/GO.21.00393

Ku, J. K., Um, I. W., Jun, M. K., & Kim, I. H. (2023). Clinical management of external apical root resorption using amniotic membrane matrix and Bio-Dentine. *Journal of Current Research in Oral Surgery, 3*, 1–5. doi:10.51847/lOSwt6Qzpv

Landry, M., Spinella, M., Kumaran, K., Levesque, V., & Tyebkhan, J. M. (2024). Studying the effectiveness of mindfulness intervention on the stress of mothers with premature infants. *Journal of Integrative Nursing and Palliative Care, 5*(1), 48–54. doi:10.51847/YRsdPlmIDO

Lee, J., Gillam, L., Visvanathan, K., Hansford, J. R., & McCarthy, M. C. (2021). Clinical utility of precision medicine in pediatric oncology: A systematic review. *JCO Precision Oncology, 5*, 1088–1102. doi:10.1200/PO.20.00405

Lee, M. J., & Ferreira, J. (2024). COVID-19 and children as an afterthought: Establishing an ethical framework for pandemic policy that includes children. *Asian Journal of Ethics in Health and Medicine, 4*, 1–19. doi:10.51847/haLKYCQorD

Lee, S., Kim, J., & Byun, G. (2023). The interplay of political skill, ethical leadership, and leader-member exchange in shaping work outcomes. *Annals of Organizational Culture, Leadership and External Engagement Journal, 4*, 45–53. doi:10.51847/vAKE892Paf

Litière, S., & Bogaerts, J. (2022). Imaging endpoints for clinical trial use: A RECIST perspective. *Journal for ImmunoTherapy of Cancer, 10*(11), e005092. doi:10.1136/jitc-2022-005092

Liu, D., Zhou, X., Liu, Y., Wang, H., Liu, J., Li, Z., Liu, Y., Hou, X., & Hao, Y. (2026). An MRI radiomics approach to predict the efficacy of chemotherapy for osteosarcoma. *Pathology - Research and Practice, 277*, 156279. doi:10.1016/j.prp.2025.156279

McNamara, C., Mankad, K., Thust, S., Dixon, L., Limback-Stanic, C., D'Arco, F., Jacques, T. S., & Löbel, U. (2022). 2021 WHO classification of tumours of the central nervous system: A review for the neuroradiologist. *Neuroradiology, 64*(10), 1919–1950. doi:10.1007/s00234-022-03008-6

Mojsak, D., Dębczyński, M., Kuklińska, B., & Mróz, R. M. (2022). Ewing's sarcoma in a 58-year-old man: Challenges of cancer diagnosis during the COVID-19 era. *Archives of International Journal of Cancer and Allied Sciences, 2*(1), 37–41. doi:10.51847/J1EMRn8tE2

Ncube, M., Sibanda, M., & Matenda, F. R. (2023). The influence of AI and the pandemic on BRICS nations: South Africa's economic performance during crisis. *Annals of Organizational Culture, Leadership and External Engagement Journal, 4*, 17–24. doi:10.51847/lrMvYTE3OF

Nered, S. N., Volkov, A. Y., Kozlov, N. A., Stilidi, I. S., & Arhiri, P. P. (2023). TNM classification of malignant tumors:

Eighth edition for retroperitoneal liposarcoma. Ways to improve. *Asia-Pacific Journal of Clinical Oncology, 19*(5), e267–e272. doi:10.1111/ajco.13898

Ngan, E., Mullikin, D., Theruvath, A. J., Annapragada, A. V., Ghaghada, K. B., Heczey, A. A., & Starosolski, Z. A. (2025). MRI-based radiomics for outcome stratification in pediatric osteosarcoma. *Cancers, 17*(15), 2586. doi:10.3390/cancers17152586

Oberoi, S., Crane, J. N., Haduong, J. H., Rudzinski, E. R., Wolden, S. L., Dasgupta, R., Linardic, C. M., Weiss, A. R., Venkatramani, R., & Children's Oncology Group Soft Tissue Sarcoma Committee. (2023). Children's Oncology Group's 2023 blueprint for research: Soft tissue sarcomas. *Pediatric Blood & Cancer, 70*(Suppl. 6), e30556. doi:10.1002/pbc.30556

Olaya Vargas, A., Salazar-Rosales, H., Caballero-Palacios, M., Ramírez-Uribe, N., López-Hernández, G., Morales-Martinez, E., Cervantes-Delgado, M., Velasco Hidalgo, L., Castellanos-Toledo, A., Cárdenas-Cardos, R., et al. (2025). High-risk neuroblastoma in Mexico: From multimodal treatment to immunotherapy. Regarding the first case treated with naxitamab. *Frontiers in Oncology, 15*, 1520171. doi:10.3389/fonc.2025.1520171

Oran, I. B., & Azer, O. A. (2023). The evolution of Turkey's role in international development: A globalization perspective. *Annals of Organizational Culture, Leadership and External Engagement Journal, 4*, 1–8. doi:10.51847/oNOPb4T9g1

Purkayastha, S., Shalu, H., Gutman, D., Holodny, A., Modak, S., Basu, E., Kushner, B., Kramer, K., Haque, S., & Stember, J. N. (2024). Evolutionary strategies AI addresses multiple technical challenges in deep learning deployment: Proof-of-principle demonstration for neuroblastoma brain metastasis detection. *Journal of Imaging Informatics in Medicine, 37*(6), 2920–2930. doi:10.1007/s10278-024-01165-z

Ribeiro, A., Martins, S., & Fonseca, T. (2024). Progress and gaps in national medicines policy implementation in SADC member states: A comprehensive desktop review. *Interdisciplinary Research in Medical Sciences Specialties, 4*(1), 42–56. doi:10.51847/0eVBxAI8y0

Rockall, A. G., Shelmerdine, S. C., & Chen, M. (2023). AI and ML in radiology: Making progress. *Clinical Radiology, 78*(2), 81–82. doi:10.1016/j.crad.2022.10.010

Rosellini, E., Giordano, C., Guidi, L., & Cascone, M. G. (2024). Creation of a novel surgical suture material designed to inhibit arterial thrombosis formation. *Journal of Medical Science Interdisciplinary Research, 4*(1), 1–7. doi:10.51847/7denx72XdE

Sanlier, N., & Yasan, N. (2024). Exploring the link between COVID-19 and vitamin D: A concise overview. *Interdisciplinary Research in Medical Sciences Specialties, 4*(1), 23–32. doi:10.51847/skW1PmtWeB

Sharon, C. E., Straker, R. J., III, & Karakousis, G. C. (2022). The role of imaging in soft tissue sarcoma diagnosis and management. *Surgical Clinics of North America, 102*(4), 539–550. doi:10.1016/j.suc.2022.04.003

Simonyan, R., Babayan, M., Yekmalyan, H., Alexanyan, A., Simonyan, G., Alexanyan, S., Darbinyan, L., Simonyan, K., & Simonyan, M. (2023). Identification and Extraction of Superoxide-Generating Protein Assemblies from *Helianthus tuberosus*, *Daucus sativus*, and *Solanum tuberosum*. *Specialty Journal of Pharmacognosy, Phytochemistry, and Biotechnology, 3*, 15-20.

Stogiannos, N., Cuocolo, R., Akinci D'Antonoli, T., Pinto Dos Santos, D., Harvey, H., Huisman, M., Kocak, B., Kotter, E., Lekadir, K., Shelmerdine, S. C., et al. (2025). Recognising errors in AI implementation in radiology: A narrative review. *European Journal of Radiology, 191*, 112311. doi:10.1016/j.ejrad.2025.112311

Suchy, W., & Jurkowski, O. (2024). Clinical assessment of 5% lidocaine patches for postoperative analgesia: Efficacy, effectiveness, and safety. *Bulletin of Pioneer Research in Medical and Clinical Sciences, 4*(1), 31–36. doi:10.51847/UxKg3AkOTB

Sultangaziyeva, A., Sambetbayeva, M., Mukazhanov, N., Abdygalym, B., & Serikbayeva, S. (2026). A multi-layer annotated corpus for information extraction in Russian clinical NLP. *Frontiers in Artificial Intelligence, 9*, 1766899. doi:10.3389/frai.2026.1766899

Szklener, K., Nieoczym, K., Niedziela, K., Światłowski, Ł., & Mańdziuk, S. (2023). Exceptional survival with lorlatinib in ALK-rearranged lung cancer: A case report. *Asian Journal of Current Research in Clinical Cancer, 3*(1), 1–5. doi:10.51847/DxGARc9jsQ

Thazha, S. K., Cruz, J. P., Alquwez, N., Scaria, B., Rengan, S. S., & Almazan, J. U. (2023). Studying the attitude and knowledge of nursing students towards the physical restraint use in patients. *Journal of Integrative Nursing and Palliative Care, 4*, 1–5. doi:10.51847/cFz2ew4AK8

Tsiganock, A. S., Bgantseva, A. E., Vostrikova, V. R., Shevel, D. S., Saidarova, A. I., Bekbuzarov, I. M., Kurbanov, T. K., & Shadova, S. M. (2023). Exploring the Wound Healing Potential of Aqueous Extracts from Caucasus Herbs in Diabetes Mellitus. *Specialty Journal of Pharmacognosy, Phytochemistry, and Biotechnology, 3*, 31-38. doi:10.51847/Y5Fvcyw12s

Tsukamoto, T., & Miki, Y. (2023). Imaging of pituitary tumors: An update with the 5th WHO classification—Part 1. Pituitary neuroendocrine tumor (PitNET)/pituitary adenoma. *Japanese Journal of Radiology, 41*(8), 789–806. doi:10.1007/s11604-023-01400-7

Tsvetkova, D., Vezenkov, L., Ivanov, T., Danalev, D., & Kostadinova, I. (2023). Evaluation of cytotoxic activity of galantamine peptide esters: GAL-LEU and GAL-VAL against PC3 cell line. *Asian Journal of Current Research in Clinical Cancer, 3*(1), 24–33. doi:10.51847/V6Qg7e4512

Tun, H. M., Rahman, H. A., Naing, L., & Malik, O. A. (2026). Health economics evaluation of artificial intelligence in the field of oncology: A scoping review. *Health Economics Review, 16*(1), 52. doi:10.1186/s13561-026-00751-x

Umarova, M. S., Akhyadova, Z. S., Salamanova, T. O., Dzhamaldinova, Z. I., Taysumova, Z. D., Bekmurzaeva, M. R., Tapaeva, M. M., & Ivanushkina, A. M. (2024). Influence of Vibrations and Other Negative Physical Factors of Production on Protein Metabolism and Protein Dynamics in the Body. *Journal of Medical Sciences and Interdisciplinary Research, 4*(1), 39-44.

doi:10.51847/Jk38F1v5XH

Uneno, Y., Morita, T., Watanabe, Y., Okamoto, S., Kawashima, N., & Muto, M. (2024). Assessing the supportive care needs of elderly cancer patients at Seirei Mikatahara General Hospital in 2023. *International Journal of Social and Psychological Aspects of Healthcare, 4*, 13–19. doi:10.51847/o4njwxvRSF

Veiga-Canuto, D., Cerdà-Alberich, L., Jiménez-Pastor, A., Carot Sierra, J. M., Gomis-Maya, A., Sangüesa-Nebot, C., Fernández-Patón, M., Martínez de Las Heras, B., Taschner-Mandl, S., Düster, V., et al. (2023). Independent validation of a deep learning nnU-Net tool for neuroblastoma detection and segmentation in MR images. *Cancers, 15*(5), 1622. doi:10.3390/cancers15051622

Vered, M., & Wright, J. M. (2022). Update from the 5th edition of the World Health Organization classification of head and neck tumors: Odontogenic and maxillofacial bone tumours. *Head and Neck Pathology, 16*(1), 63–75. doi:10.1007/s12105-021-01404-7

Wang, P., Chen, X., Yan, X., Yan, J., Yang, S., Mao, J., Li, F., & Su, X. (2026). Comprehensive analysis of [18F]MFBG biodistribution normal patterns and variability in pediatric patients with neuroblastoma. *European Journal of Nuclear Medicine and Molecular Imaging, 53*(2), 1041–1052. doi:10.1007/s00259-025-07490-x

Wang, Y., Wang, F., Qin, Z., Fu, Y., Wang, J., Li, S., & Zhang, D. (2025). A non-invasive diagnostic approach for neuroblastoma utilizing preoperative enhanced computed tomography and deep learning techniques. *Scientific Reports, 15*(1), 14652. doi:10.1038/s41598-025-99451-5

Wiggins, W. F., Kitamura, F., Santos, I., & Prevedello, L. M. (2021). Natural language processing of radiology text reports: Interactive text classification. *Radiology: Artificial Intelligence, 3*(4), e210035. doi:10.1148/ryai.2021210035

Wright, A., Desai, M., Bolan, C. W., Badawy, M., Guccione, J., Rao Korivi, B., Pickhardt, P. J., Mellnick, V. M., Lubner, M. G., Chen, L., et al. (2022). Extraskeletal Ewing sarcoma from head to toe: Multimodality imaging review. *Radiographics, 42*(4), 1145–1160. doi:10.1148/rg.210226

Würtemberger, J., Ripperger, T., Vokuhl, C., Bauer, S., Teichert-von Lüttichau, I., Wardelmann, E., Niemeyer, C. M., Kratz, C. P., Schlegelberger, B., & Hettmer, S. (2023). Genetic susceptibility in children, adolescents, and young adults diagnosed with soft-tissue sarcomas. *European Journal of Medical Genetics, 66*(5), 104718. doi:10.1016/j.ejmg.2023.104718

Yan, L., Dong, X., & Chen, S. (2026). Advances in osteosarcoma research: Pathogenesis and emerging therapeutic strategies. *Critical Reviews in Oncology/Hematology, 222*, 105252. doi:10.1016/j.critrevonc.2026.105252

Yüksel, H., & Tongal, S. N. (2022). Pulmonary nodules in children. *Tuberkuloz ve Toraks, 70*(4), 382–391. doi:10.5578/tt.20229610

Zafar, A., Wang, W., Liu, G., Wang, X., Xian, W., McKeon, F., Foster, J., Zhou, J., & Zhang, R. (2021). Molecular targeting therapies for neuroblastoma: Progress and challenges. *Medical Research Reviews, 41*(2), 961–1021. doi:10.1002/med.21750

Zarghooni, K., Bratke, G., Landgraf, P., Simon, T., Maintz, D., & Eysel, P. (2023). The diagnosis and treatment of osteosarcoma and Ewing's sarcoma in children and adolescents. *Deutsches Ärzteblatt International, 120*(24), 405–412. doi:10.3238/arztebl.m2023.0079