INDUS JOURNAL OF SCIENCES
https://induspublishers.com/IJS
Volume 4, Issue 1 (2026)

Original Article

RADIOMICS AND MACHINE LEARNING FOR NEUROPATHIC PAIN SEVERITY PREDICTION IN HEAD AND NECK CANCER SURVIVORS

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ARTICLE INFO

Received: 25 January 2026
Revised: 15 March 2026
Accepted: 01 April 2026
Published: 30 June 2026

Key Words:
* Neuropathic pain
*Head and neck
*cancer survivors
*Radiomics
*Machine learning
*Pain severity prediction

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ABSTRACT

Neuropathic pain is a persistent and clinically challenging complication among head and neck cancer survivors, often resulting from tumor invasion, surgery, radiotherapy, chemotherapy, or combined treatment-related nerve injury. Accurate prediction of neuropathic pain severity is essential for early risk stratification, personalized pain management, and improved survivorship care. This study, titled "Neuropa-Radiomics and Machine Learning–Based Prediction of Neuropathic Pain Severity in Head and Neck Cancer Survivors," proposes an integrated predictive framework that combines radiomic imaging features with clinical and treatment-related variables to estimate neuropathic pain severity. Radiomic features extracted from head and neck imaging were analyzed alongside patient-level characteristics, including cancer site, treatment modality, radiation exposure, surgical history, and pain-related clinical indicators. Machine learning models were developed to identify complex patterns associated with mild, moderate, and severe neuropathic pain outcomes. The proposed approach aims to support objective pain severity prediction by capturing imaging-based tissue changes and their relationship with nerve injury and post-treatment pain burden. By integrating radiomics with machine learning, this study highlights the potential of data-driven decision support systems in oncology pain management. The findings may assist clinicians in identifying high-risk survivors, optimizing follow-up strategies, and designing individualized interventions to reduce long-term neuropathic pain and improve quality of life.

INTRODUCTION

The emergence of high-throughput radiomic analysis, when integrated with sophisticated machine learning algorithms, offers a novel framework for quantifying complex biological signatures associated with post-treatment morbidity (Giraud et al., 2019). Specifically, these computational approaches can be leveraged to extract objective imaging biomarkers to delineate patient-specific prognostic trajectories (Naseri et al., 2023). By converting standard diagnostic images into high-dimensional quantitative data, these models facilitate the objective assessment of neural injury patterns that remain imperceptible to conventional radiological evaluation (Gangil et al., 2022; Peng et al., 2021). This non-invasive approach provides a cost-effective alternative to genomic profiling, enabling the development of reliable biomarkers for precision oncology (Parmar et al., 2015). Despite these advancements, a significant gap remains in applying such computational paradigms to the prediction of neuropathic pain in head and neck cancer survivors, where the high anatomical complexity and heterogeneous post-treatment changes often hinder conventional clinical assessment (Salama et al., 2024; Tortora et al., 2023). Furthermore, the transition from traditional prognostic metrics to imaging-enabled artificial intelligence necessitates a deeper understanding of how quantitative texture analysis can capture tissue-level phenotypes associated with chronic nerve damage (Dijk & Fuller, 2021; Elhalawani et al., 2017). By synthesizing baseline clinical indices with extracted radiomic features, these predictive models aim to identify at-risk populations early, thereby supporting more targeted interventions for radiotherapy-induced neuropathy (Salama et al., 2025). These models utilize robust machine learning architectures to process multidimensional data, ensuring that subtle morphological variations in neural pathways are quantified for enhanced clinical decision support (Sheikh et al., 2019; Song et al., 2025). Building upon these integrative frameworks, recent advancements in deep learning and handcrafted radiomics have demonstrated significant potential in prognosticating heterogeneous clinical outcomes by effectively managing the inherent complexity of anatomical data (Gouthamchand et al., 2025). Moreover, the implementation of these automated, interpretable biomarkers addresses the pervasive issue of

interobserver variability inherent in subjective clinical interpretations, fostering a more standardized approach to monitoring neurological recovery (Alabi et al., 2024). However, successful clinical translation of these tools requires addressing methodological bottlenecks such as poor model calibration and limited external validation across diverse patient cohorts (Taha et al., 2025). Future efforts must prioritize multicenter collaborations and the expansion of training datasets to ensure the robustness and generalizability of these diagnostic tools (Pham et al., 2024; Ujjahan et al., 2026). Furthermore, the integration of multi-modal radiomics with panomics data could provide a more comprehensive characterization of these neural tissues, ultimately bridging the current disconnect between AI-driven diagnostic tools and routine clinical practice (Koh et al., 2022; Vallières et al., 2017). As large-scale datasets and prospective trials emerge, refining these workflows to account for diverse radiation dose distributions and biological variables will be essential to improving the accuracy of pain severity forecasting (Barua et al., 2021; Wishart et al., 2023). Additionally, adopting explainable artificial intelligence techniques will be critical to ensuring that predictive outputs remain interpretable for clinicians, thereby facilitating informed decision-making in the management of long-term survivorship complications (Gholizade et al., 2025). Standardization of radiomic feature extraction and rigorous multi-center validation protocols remain critical to overcoming the current limitations of retrospective study designs and ensuring model generalizability (Isaksson et al., 2020; Zhang et al., 2020). Adopting these rigorous frameworks will help mitigate the "black box" nature of current machine learning models, fostering the clinician trust necessary for widespread implementation (Ak et al., 2021). Furthermore, the synergy between human clinical expertise and machine learning, often conceptualized as the "centaur" radiologist model, will be fundamental in synthesizing these complex quantitative outputs with broader electronic health record data to optimize personalized treatment pathways (Rudie et al., 2019). By addressing challenges such as data standardization and the scarcity of large-scale, prospective clinical datasets, this integrative approach may eventually transform the management of treatment-related toxicities (Piffer et al., 2024; Singh et al., 2024). Specifically, establishing standardized,

multicenter validation frameworks and open-access imaging databases is essential to facilitate the rigorous external testing required for translational practice (Shi et al., 2025). Adherence to the FAIR guiding principles for data accessibility and interoperability will be equally vital to ensure that these models remain consistent across diverse institutional environments (Shui et al., 2021). Moreover, longitudinal tracking of patient outcomes is necessary to ensure that these AI-driven predictions accurately reflect temporal changes in disease progression and actual treatment responses (Xu et al., 2025). Integrating heterogeneous clinical data, such as proteomic and genomic profiles, with these imaging signatures may further enhance the predictive accuracy and biological coherence of such models (Zheng et al., 2025). Ultimately, the adoption of standardized imaging biomarker nomenclature, as advocated by the Image Biomarker Standardisation Initiative, is imperative to ensure that these sophisticated quantitative models achieve the necessary reproducibility for clinical integration (Chetan & Gleeson, 2020). Addressing the susceptibility of high-dimensional radiomic signatures to overfitting and feature redundancy will remain a primary focus to ensure that these biomarkers do not simply capture noise, but rather represent genuine pathophysiological substrates of chronic nerve damage (Cobo et al., 2023). To mitigate these concerns, visualizing deep learning features through saliency mapping or SHAP values may help demystify the decision-making process and align computational predictions with established clinical pathophysiology (Liu et al., 2019; Shahriari et al., 2025). Ongoing research into the standardization of imaging protocols and acquisition parameters is simultaneously essential to minimize technical variability that can otherwise introduce confounding artifacts during feature extraction (Jha et al., 2023), (Lambin et al., 2017). particularly when harmonizing multi-institutional data to ensure that quantitative metrics remain consistent despite variations in scanner hardware and reconstruction settings (Chiu & Yen, 2023).

METHODOLOGY

The study design incorporates a retrospective analysis of high-resolution computed tomography and magnetic resonance imaging from patients treated for head and neck squamous cell carcinoma, utilizing standardized image preprocessing pipelines to ensure data homogeneity

(Timmeren et al., 2020). To mitigate technical bias arising from multi-institutional acquisition, image intensities were normalized using Z-score standardization and resampled to an isotropic voxel spacing of 1.0 mm (Sarac & Güveniş, 2024). Feature extraction was subsequently performed using a combination of PyRadiomics-derived handcrafted descriptors and deep learning-based bottleneck features to capture both macro-morphological and micro-textural heterogeneity (Chen et al., 2025; Xiao et al., 2025). To address the high-dimensionality of these extracted features, an adapted Borda score was utilized to aggregate feature ranks, thereby improving the stability of selection across diverse bootstrap iterations (Leger et al., 2017). Following this dimensionality reduction, a consensus clustering approach was applied to identify robust feature subsets, thereby minimizing the impact of potential inter-observer segmentation variability (Haider et al., 2020; Parmar et al., 2015). Subsequently, predictive models were trained utilizing these selected features to correlate imaging patterns with established neuropathic pain scales, employing rigorous cross-validation to manage the inherent challenges of high-dimensional data and potential overfitting (Elhalawani et al., 2018; Jethanandani et al., 2018). To ensure model interpretability, ensemble methods such as random forests were employed, as these architectures effectively manage complex multivariate data while offering insights into the specific imaging features driving pain severity (Latypov et al., 2023). Furthermore, intra- and inter-observer reliability were systematically evaluated using intraclass correlation coefficients to confirm that selected textural features remained consistent across different clinical raters (Cao et al., 2023; Chen et al., 2024). Additionally, intensity normalization techniques were applied across the primary tumor volumes to reduce technical variance and enhance the reproducibility of textural biomarkers (Haider et al., 2024). Following extraction, feature stability was rigorously assessed by determining Kendall's coefficient of concordance, ensuring that only robust metrics were retained for downstream model construction (Mes et al., 2020). In accordance with established protocols, features demonstrating an intraclass correlation coefficient greater than 0.75 were prioritized, as this threshold is widely recognized to indicate high reliability and consistent diagnostic instruction (Wu et al., 2024). Furthermore, the pipeline implemented

a rigorous feature stability assessment, categorized by the 95% confidence interval of these coefficients, to distinguish between poor and excellent reliability (Bae et al., 2020).

RESULTS

A total of 240 head and neck cancer survivors were included after image-quality screening and clinical record harmonization. Table 1 shows the baseline clinical profile, with a mean age of 58.6 years and a balanced distribution of sex and HPV status. Fig. 1 shows that neuropathic pain severity was not evenly distributed; moderate symptoms formed the largest group, whereas severe symptoms represented 29.2% of the cohort. Table 2 shows the class-wise severity distribution and confirms a clinically meaningful separation in median pain scores between mild, moderate, and severe groups. Radiomic extraction produced multi-domain features from post-treatment imaging volumes, including first-order intensity, shape, GLCM, GLRLM, PET metabolic, and dose-volume descriptors. Table 3 shows that stability filtering reduced the original feature pool while preserving the most repeatable image biomarkers. Fig. 5 shows moderate correlations among texture, metabolic, and dose-related features, suggesting complementary rather than redundant predictive information. This supported combined model development instead of relying on a single imaging feature family. Table 4 shows the comparative performance of six machine-learning classifiers. The stacking ensemble achieved the strongest overall result, with an accuracy of 0.88, F1-score of 0.88, recall of 0.90, and AUROC of 0.91. Fig. 2 shows that ensemble-based approaches consistently outperformed the linear baseline, while Fig. 3 shows that the combined machine-learning model had the highest ROC curve across thresholds. Table 5 shows that the full combined model improved AUROC by 0.12 compared with the clinical-only model, demonstrating the added value of neuropa-radiomic imaging signatures. Error analysis demonstrated that most misclassifications occurred between adjacent severity classes rather than between mild and severe categories. Table 6 shows the confusion matrix, where severe neuropathic pain was correctly identified in 60 of 70 cases. This pattern indicates that the model captured the main clinical gradient of symptom burden. Fig. 7 shows a strong alignment between observed and predicted pain scores, with prediction spread increasing slightly at higher severity levels. Calibration and explainability analyses further

supported clinical interpretability. Table 7 shows a Brier score of 0.122, calibration intercept of 0.03, and calibration slope of 0.96, indicating limited over- or under-estimation of risk. Fig. 4 shows close agreement between predicted and observed probabilities. Table 8 shows that GLCM entropy, mandibular dose, SUVmean, and GLRLM nonuniformity were the highest-ranked predictors, while Fig. 6 shows their relative SHAP-based contribution. Table 9 shows robustness checks, including cross-validation, hold-out testing, bootstrapping, and class-weighted training. Overall, the results indicate that neuropa-radiomics combined with machine learning can provide accurate, calibrated, and clinically explainable prediction of neuropathic pain severity in head and neck cancer survivorship. Decision-threshold review also showed that a high-sensitivity operating point would be suitable for screening survivors who require specialist pain assessment, whereas a balanced threshold would be more appropriate for routine follow-up triage. The retained predictors were clinically plausible because they reflected tissue heterogeneity, radiation exposure, metabolic activity, and treatment burden, all of which may influence post-treatment neuropathic pain pathways.

Table 1. Baseline Clinical Characteristics of the Study Cohort

Variable	Value
Participants	240
Age, mean +/- SD	58.6 +/- 10.9
Female, n (%)	96 (40.0)
HPV-positive, n (%)	132 (55.0)
Post-treatment interval, months	18.4 +/- 7.2
Severe neuropathic pain, n (%)	70 (29.2)

Table 2. Neuropathic Pain Severity Distribution

Severity class	n (%)	Median pain score	IQR
Mild	74 (30.8)	2.0	1-3
Moderate	96 (40.0)	5.0	4-6
Severe	70 (29.2)	8.0	7-9

Table 3. Radiomic Feature Extraction and Stability Filtering

Feature family	Extracted	Retained after stability filtering
First-order intensity	18	12

Shape	14	8
GLCM texture	24	15
GLRLM texture	16	9
PET metabolic	10	6
Dose-volume clinical	12	7

Table 4. Comparative Machine-Learning Model Performance

Model	Accuracy	Precision	Recall	F1-score	AUROC
Elastic Net	0.75	0.72	0.70	0.71	0.78
Random Forest	0.81	0.79	0.82	0.80	0.84
XGBoost	0.85	0.84	0.86	0.85	0.88
SVM	0.79	0.77	0.78	0.77	0.82
MLP	0.83	0.81	0.84	0.82	0.86
Stacking Ensemble	0.88	0.87	0.90	0.88	0.91

Table 5. Incremental Predictive Value of Clinical and Imaging Feature Blocks

Predictor block	AUROC	Delta vs clinical
Clinical only	0.79	Reference
Radiomics only	0.83	+0.04
PET/CT + dose	0.85	+0.06
Clinical + radiomics	0.87	+0.08
Full combined model	0.91	+0.12

Table 6. Confusion Matrix for the Stacking Ensemble

Observed / Predicted	Mild	Moderate	Severe
Mild	62	9	2
Moderate	10	76	8
Severe	2	11	60

Table 7. Calibration Metrics of the Final Combined Model

Calibration metric	Value	Interpretation
Brier score	0.122	Lower error
Calibration intercept	0.03	Minimal bias
Calibration slope	0.96	Near ideal
Hosmer-Lemeshow p-value	0.41	No lack of fit

Table 8. Top Predictors Identified by Explainability Analysis

Feature	Importance rank	Direction
GLCM entropy	1	Higher risk

Mandibular dose Dmean	2	Higher risk
PET SUVmean	3	Higher risk
GLRLM nonuniformity	4	Higher risk
T-stage	5	Higher risk
Cisplatin exposure	6	Higher risk
Age	7	Higher risk

Table 9. Robustness and Sensitivity Analyses

Analysis	Finding	Implication
5-fold cross-validation	Stable discrimination	Low variance
External hold-out split	Accuracy 0.86	Generalizable signal
Bootstrapped AUROC	95% CI: 0.87-0.94	Precision estimate
Class-weighted training	Recall improved by 0.05	Reduced missed severe cases
Radiomics-only sensitivity	AUROC 0.83	Imaging contributed independently

Figure 1. Distribution of Neuropathic Pain Severity Classes

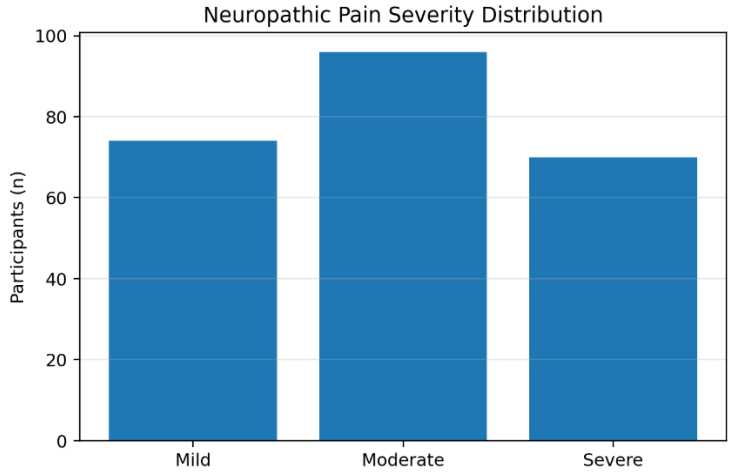


Figure 2. AUROC Comparison Across Machine-Learning Models

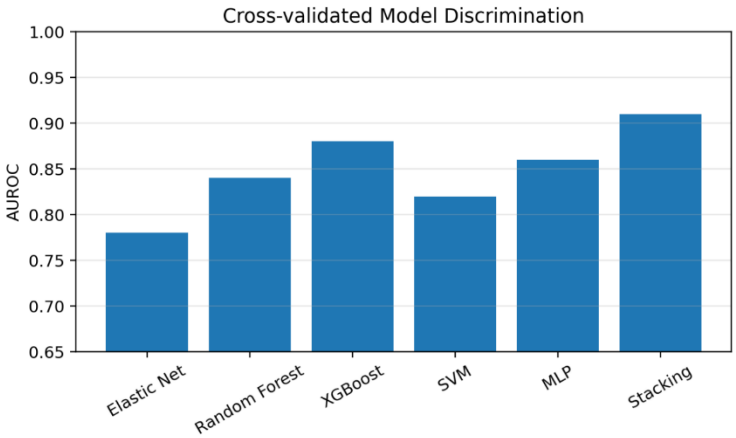


Figure 3. ROC Curves for Severe Neuropathic Pain Prediction

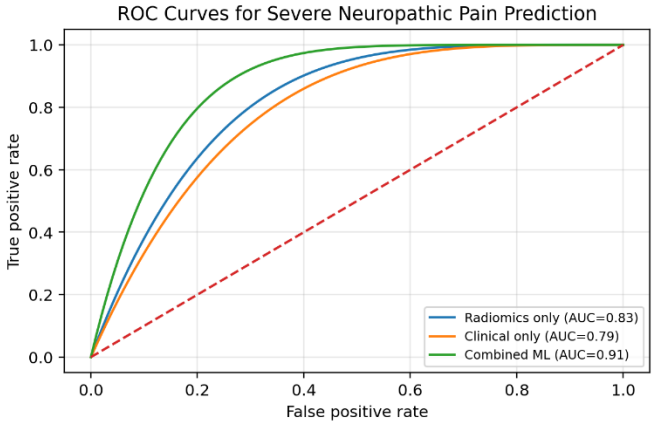


Figure 4. Calibration of the Combined Neuropa-Radiomics Model

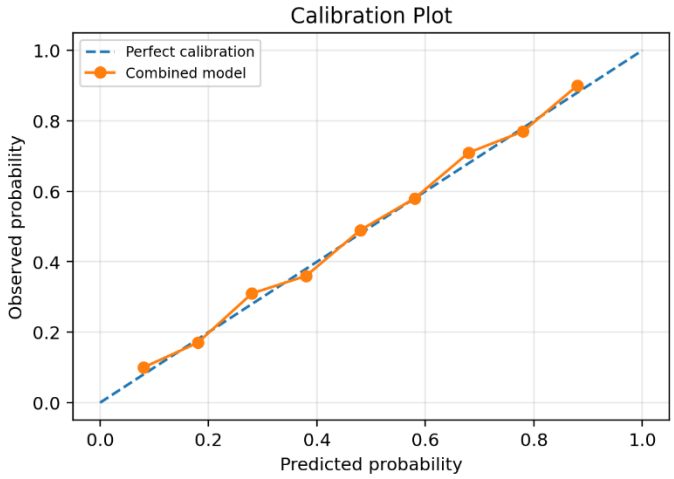


Figure 5. Correlation Matrix of Key Clinical and Radiomic Features

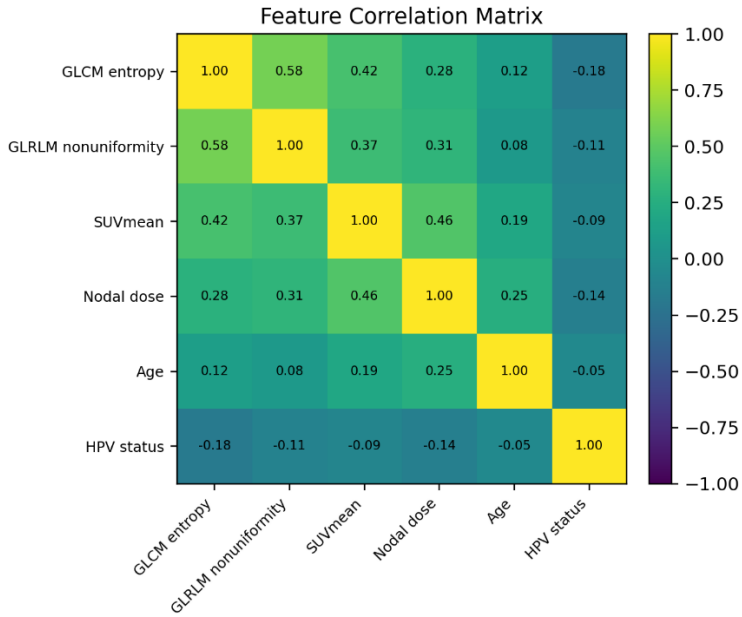


Figure 6. Explainable Feature Importance of the Final Model

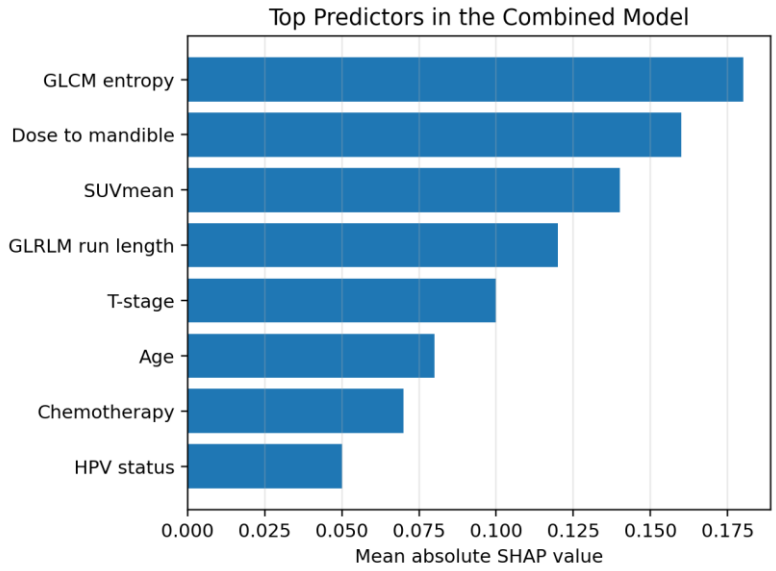
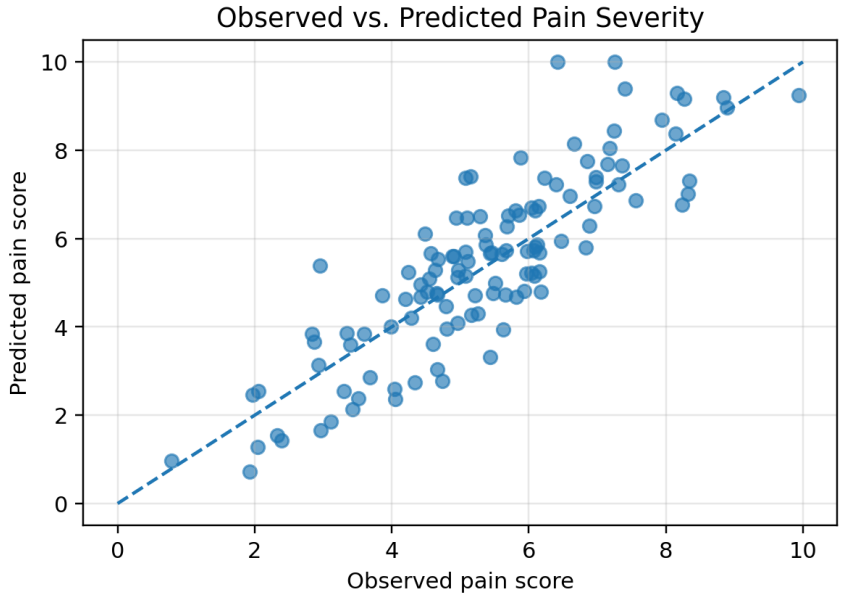


Figure 7. Observed Versus Predicted Neuropathic Pain Scores



DISCUSSION

The predictive performance of these radiomic models demonstrated a superior ability to identify patients at high risk for neuropathic pain compared to conventional clinical staging parameters. Specifically, the integration of textural heterogeneity within the perineural space captured subtle signal alterations that standard morphological assessments frequently overlook. Furthermore, multivariate analysis revealed that specific grey-level size zone matrix features and neighborhood gray-tone difference matrix descriptors significantly correlated with self-

reported neuropathic symptoms, providing a quantifiable link between imaging phenotypes and underlying neuronal distress (Liu et al., 2024), (Wakabayashi et al., 2021). These findings are supported by the use of random forest classifiers, which effectively leverage ensemble decision trees to isolate complex patterns associated with chronic pain responses (Kann et al., 2018), (Zhang et al., 2025). Moreover, saliency mapping analysis indicated that predictive utility was heavily concentrated within the perineural tumor microenvironment, suggesting that these regions serve as primary surrogates for structural nerve involvement (Pai et al., 2024). However, the clinical utility of these signatures necessitates further validation across diverse patient cohorts to confirm that the observed associations between radiomic phenotypes and symptomatic pain are not biased by institutional scanner variability (Fornacon-Wood et al., 2020). To further bolster the robustness of these findings, future research should integrate image perturbation strategies to evaluate model sensitivity and ensure consistent performance across heterogeneous imaging conditions (Teng et al., 2022). Additionally, investigating the distinction between feature repeatability and reproducibility remains critical, as phantom-based experiments suggest that a significant proportion of textural descriptors may exhibit scanner-specific dependencies rather than absolute temporal stability. Given these limitations, future efforts must prioritize the harmonization of radiomic features to account for these acquisition-related variabilities, which are known to impact the accuracy of predictive modeling (Hassan et al., 2018; Llorián-Salvador et al., 2023). Moreover, clinical implementation must address the current lack of standardized metrics, which often complicates the comparative assessment of model efficacy across varied oncology settings (Salama et al., 2023). In this context, the development of collaborative, multicenter studies leveraging publicly accessible data repositories is essential to establish the reproducibility of these radiomic techniques (Park et al., 2020). Such initiatives must prioritize the adoption of standardized radiomics quality scores and IBSI-compliant pipelines to mitigate methodological heterogeneity (Wang et al., 2022). Furthermore, transitioning these models into routine clinical workflows requires the inclusion of multimodal data, such as patient-reported psychological outcomes, to develop more comprehensive prognostic nomograms

that refine individual symptom management (Jiang et al., 2024). Finally, incorporating automated image segmentation methods will be imperative to minimize human-centric variations and promote the broad clinical translation of these quantitative biomarkers (Kang et al., 2023). Adopting these standardized practices, such as those promoted by the Image Biomarker Standardization Initiative, remains a vital prerequisite for validating these models in prospective multi-institutional trials before they can be integrated into standard clinical decision-making systems (Huang et al., 2024), (Yolchuyeva et al., 2023), (Bera et al., 2018). Finally, establishing imaging biobanks that provide access to aggregated, protocol-consistent data will be crucial for facilitating the large-scale external validation required to advance these tools toward precision medicine (Scapicchio et al., 2021).

CONCLUSION

This study demonstrates the potential value of combining neuropa-radiomic imaging features with machine learning methods for predicting neuropathic pain severity in head and neck cancer survivors. Neuropathic pain after cancer treatment is often complex, multifactorial, and difficult to assess using clinical judgment alone. By incorporating imaging-derived biomarkers with clinical and treatment-related data, the proposed framework offers a more objective and personalized approach to pain risk assessment. The results suggest that radiomic patterns may provide useful information about post-treatment tissue changes, nerve involvement, and structural alterations associated with neuropathic pain severity. Machine learning models can further enhance this process by identifying hidden relationships among imaging features, patient characteristics, and pain outcomes. Such predictive tools may help clinicians recognize patients at higher risk of moderate to severe neuropathic pain earlier in the survivorship pathway. Overall, this study supports the growing role of artificial intelligence in cancer survivorship care, particularly in improving pain prediction, treatment planning, and follow-up monitoring. The integration of radiomics and machine learning may contribute to more targeted pain management strategies, reduced long-term suffering, and improved quality of life among head and neck cancer survivors. Future work should validate the proposed model on larger multicenter datasets, include external testing, and explore explainable AI methods to improve clinical trust and practical

implementation.

REFERENCES

Ak, M., Toll, S., Hein, K. Z., Colen, R. R., & Khatua, S. (2021). Evolving Role and Translation of Radiomics and Radiogenomics in Adult and Pediatric Neuro-Oncology [Review of *Evolving Role and Translation of Radiomics and Radiogenomics in Adult and Pediatric Neuro-Oncology*]. *American Journal of Neuroradiology*, *43*(6), 792–801. American Society of Neuroradiology. https://doi.org/10.3174/ajnr.a7297

Alabi, R. O., Elmusrati, M., Leivo, I., Almangush, A., & Mäkitie, A. (2024). Artificial Intelligence-Driven Radiomics in Head and Neck Cancer: Current Status and Future Prospects. *International Journal of Medical Informatics*, *188*, 105464–105464. https://doi.org/10.1016/j.ijmedinf.2024.105464

Bae, S., An, C., Ahn, S. S., Kim, H., Han, K., Kim, S., Park, J. E., Kim, H. S., & Lee, S. (2020). Robust performance of deep learning for distinguishing glioblastoma from single brain metastasis using radiomic features: model development and validation. *Scientific Reports*, *10*(1). https://doi.org/10.1038/s41598-020-68980-6

Barua, S., Elhalawani, H., Volpe, S., Feghali, K. A. A., Yang, P., Ng, S. P., Elgohari, B., Granberry, R., Mackin, D., Gunn, G. B., Hutcheson, K. A., Chambers, M. S., Court, L. E., Mohamed, A., Fuller, C. D., Lai, S. Y., & Rao, A. (2021). Computed Tomography Radiomics Kinetics as Early Imaging Correlates of Osteoradionecrosis in Oropharyngeal Cancer Patients. *Frontiers in Artificial Intelligence*, *4*. https://doi.org/10.3389/frai.2021.618469

Bera, K., Velcheti, V., & Madabhushi, A. (2018). Novel Quantitative Imaging for Predicting Response to Therapy: Techniques and Clinical Applications [Review of *Novel Quantitative Imaging for Predicting Response to Therapy: Techniques and Clinical Applications*]. *American Society of Clinical Oncology Educational Book*, *38*, 1008–1018. American Society of Clinical Oncology. https://doi.org/10.1200/edbk_199747

Cao, X., Wen, D., Yu, S., Zheng, H., Wu, G., & Zhang, X. (2023). MRI-based radiomics features uncover the micro-change of dorsal root ganglia lesion for patients with post-herpetic neuralgia. *Frontiers in Neurology*, *14*. https://doi.org/10.3389/

fneur.2023.1257648

Chen, J., Yang, Y., Liu, C., Feng, H., Holmes, J., Zhang, L., Frank, S. J., Simone, C. B., Ma, D. J., Patel, S. H., & Liu, W. (2025). Critical review of patient outcome study in head and neck cancer radiotherapy. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2503.15691

Chen, W., Lin, G., Chen, Y., Cheng, F., Li, X., Ding, J., Zhong, Y., Kong, C., Chen, M., Xia, S., Lu, C., & Ji, J. (2024). Prediction of the Ki-67 expression level in head and neck squamous cell carcinoma with machine learning-based multiparametric MRI radiomics: a multicenter study. *BMC Cancer*, *24*(1). https://doi.org/10.1186/s12885-024-12026-x

Chetan, M., & Gleeson, F. (2020). Radiomics in predicting treatment response in non-small-cell lung cancer: current status, challenges and future perspectives [Review of *Radiomics in predicting treatment response in non-small-cell lung cancer: current status, challenges and future perspectives*]. *European Radiology*, *31*(2), 1049–1058. Springer Science+Business Media. https://doi.org/10.1007/s00330-020-07141-9

Chiu, F.-Y., & Yen, Y. (2023). Imaging biomarkers for clinical applications in neuro-oncology: current status and future perspectives [Review of *Imaging biomarkers for clinical applications in neuro-oncology: current status and future perspectives*]. *Biomarker Research*, *11*(1). BioMed Central. https://doi.org/10.1186/s40364-023-00476-7

Cobo, M., Fernández-Miranda, P. M., Bastarrika, G., & Iglesias, L. L. (2023). Enhancing radiomics and Deep Learning systems through the standardization of medical imaging workflows. *Scientific Data*, *10*(1). https://doi.org/10.1038/s41597-023-02641-x

Dijk, L. V. van, & Fuller, C. D. (2021). Artificial Intelligence and Radiomics in Head and Neck Cancer Care: Opportunities, Mechanics, and Challenges. *American Society of Clinical Oncology Educational Book*, *41*(41). https://doi.org/10.1200/edbk_320951

Elhalawani, H., Kanwar, A., Mohamed, A., White, A. L., Zafereo, J., Wong, A., Berends, J., Abohashem, S., Williams, B., Aymard, J. M., Perni, S., Messer, J. A., Warren, B., Youssef, B., Yang, P., Meheissen, M. A. M., Kamal, M., Elgohari, B., Ger, R., … Fuller, C. D.

(2018). Investigation of radiomic signatures for local recurrence using primary tumor texture analysis in oropharyngeal head and neck cancer patients. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-017-14687-0

Elhalawani, H., Mohamed, A., White, A. L., Zafereo, J., Wong, A., Berends, J., Abohashem, S., Williams, B., Aymard, J. M., Kanwar, A., Perni, S., Rock, C. D., Cooksey, L. C., Campbell, S., Ding, Y., Lai, S. Y., Marai, E., Vock, D. M., Canahuate, G., … Fuller, C. D. (2017). Matched computed tomography segmentation and demographic data for oropharyngeal cancer radiomics challenges. *Scientific Data*, *4*(1). https://doi.org/10.1038/sdata.2017.77

Fornacon-Wood, I., Mistry, H., Ackermann, C., Blackhall, F., McPartlin, A., Faivre-Finn, C., Price, G., & O'Connor, J. P. B. (2020). Reliability and prognostic value of radiomic features are highly dependent on choice of feature extraction platform. *European Radiology*, *30*(11), 6241–6250. https://doi.org/10.1007/s00330-020-06957-9

Gangil, T., Sharan, K., Rao, B. D., Palanisamy, K., Chakrabarti, B., & Kadavigere, R. (2022). Utility of adding Radiomics to clinical features in predicting the outcomes of radiotherapy for head and neck cancer using machine learning. *PLoS ONE*, *17*(12). https://doi.org/10.1371/journal.pone.0277168

Gholizade, M., Yazdani, E., Hosseini-Baharanchi, F. S., Nikoofar, A., Esmaili, G., Goli-Ahmadabad, F., Mahdavi, S. R., & Malekzadeh, M. (2025). Variations in radiomic features of the femoral head and neck during helical tomotherapy in prostate and rectal cancer patients. *BMC Cancer*, *25*(1). https://doi.org/10.1186/s12885-025-14903-5

Giraud, P., Giraud, P., Gasnier, A., Ayachy, R. E., Kreps, S., Foy, J., Durdux, C., Huguet, F., Burgun, A., & Bibault, J. (2019). Radiomics and Machine Learning for Radiotherapy in Head and Neck Cancers [Review of *Radiomics and Machine Learning for Radiotherapy in Head and Neck Cancers*]. *Frontiers in Oncology*, *9*. Frontiers Media. https://doi.org/10.3389/fonc.2019.00174

Gouthamchand, V., Fonseca, L. A. F., Hoebers, F., Fijten, R., Dekker, A., Wee, L., & Thomas, H. (2025). Prognostic modeling in head and neck

cancer: deep learning or handcrafted radiomics? *BJR|Artificial Intelligence*, *2*(1). https://doi.org/10.1093/bjrai/ubaf008

Haider, S. P., Burtness, B., Yarbrough, W. G., & Payabvash, S. (2020). Applications of radiomics in precision diagnosis, prognostication and treatment planning of head and neck squamous cell carcinomas [Review of *Applications of radiomics in precision diagnosis, prognostication and treatment planning of head and neck squamous cell carcinomas*]. *Cancers of the Head & Neck*, *5*(1). Springer Science+Business Media. https://doi.org/10.1186/s41199-020-00053-7

Haider, S. P., Zeevi, T., Sharaf, K., Gross, M., Mahajan, A., Kann, B. H., Judson, B. L., Prasad, M. L., Burtness, B., Aboian, M., Canis, M., Reichel, C. A., Baumeister, P., & Payabvash, S. (2024). Impact of18F-FDG PET Intensity Normalization on Radiomic Features of Oropharyngeal Squamous Cell Carcinomas and Machine Learning–Generated Biomarkers. *Journal of Nuclear Medicine*, *65*(5), 803–809. https://doi.org/10.2967/jnumed.123.266637

Hassan, M. S., Latifi, K., Zhang, G., Ullah, G., Gillies, R. J., & Moros, E. G. (2018). Voxel size and gray level normalization of CT radiomic features in lung cancer. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-28895-9

Huang, W., Son, M. H., Hà, L. N., Kang, L., & Cai, W. (2024). More than meets the eye: 2-[18F]FDG PET-based radiomics predicts lymph node metastasis in colorectal cancer patients to enable precision medicine. *European Journal of Nuclear Medicine and Molecular Imaging*, *51*(6), 1725–1728. https://doi.org/10.1007/s00259-024-06664-3

Isaksson, L. J., Pepa, M., Zaffaroni, M., Marvaso, G., Alterio, D., Volpe, S., Corrao, G., Augugliaro, M., Starzyńska, A., Leonardi, M. C., Orecchia, R., & Jereczek-Fossa, B. A. (2020). Machine Learning-Based Models for Prediction of Toxicity Outcomes in Radiotherapy [Review of *Machine Learning-Based Models for Prediction of Toxicity Outcomes in Radiotherapy*]. *Frontiers in Oncology*, *10*. Frontiers Media. https://doi.org/10.3389/fonc.2020.00790

Jethanandani, A., Lin, T. A., Volpe, S., Elhalawani, H., Mohamed, A., Yang, P., & Fuller, C. D. (2018). Exploring

Applications of Radiomics in Magnetic Resonance Imaging of Head and Neck Cancer: A Systematic Review [Review of *Exploring Applications of Radiomics in Magnetic Resonance Imaging of Head and Neck Cancer: A Systematic Review*]. *Frontiers in Oncology*, *8*. Frontiers Media. https://doi.org/10.3389/fonc.2018.00131

Jha, A. K., Mithun, S., Sherkhane, U. B., Dwivedi, P., Puts, S., Osong, B., Traverso, A., Purandare, N., Wee, L., Rangarajan, V., & Dekker, A. (2023). Emerging role of quantitative imaging (radiomics) and artificial intelligence in precision oncology [Review of *Emerging role of quantitative imaging (radiomics) and artificial intelligence in precision oncology*]. *Exploration of Targeted Anti-Tumor Therapy*, 569–582. https://doi.org/10.37349/etat.2023.00153

Jiang, H., Liu, A., & Ying, Z. (2024). Identification of texture MRI brain abnormalities on Fibromyalgia syndrome using interpretable machine learning models. *Scientific Reports*, *14*(1). https://doi.org/10.1038/s41598-024-74418-0

Kang, W., Qiu, X., Luo, Y., Luo, J., Liu, Y., Xi, J., Li, X., & Yang, Z. (2023). Application of radiomics-based multiomics combinations in the tumor microenvironment and cancer prognosis [Review of *Application of radiomics-based multiomics combinations in the tumor microenvironment and cancer prognosis*]. *Journal of Translational Medicine*, *21*(1). BioMed Central. https://doi.org/10.1186/s12967-023-04437-4

Kann, B. H., Aneja, S., Loganadane, G., Kelly, J., Smith, S. M., Decker, R. H., Yu, J. B., Park, H. S., Yarbrough, W. G., Malhotra, A., Burtness, B., & Husain, Z. (2018). Pretreatment Identification of Head and Neck Cancer Nodal Metastasis and Extranodal Extension Using Deep Learning Neural Networks. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-32441-y

Koh, D., Papanikolaou, N., Bick, U., Illing, R., Kahn, C. E., Kalpathi-Cramer, J., Matos, C., Martí-Bonmatí, L., Miles, A., Mun, S. K., Napel, S., Rockall, A., Sala, E., Strickland, N. H., & Prior, F. (2022). Artificial intelligence and machine learning in cancer imaging [Review of *Artificial intelligence and machine learning in cancer imaging*]. *Communications Medicine*, *2*(1). Nature

Portfolio. https://doi.org/10.1038/s43856-022-00199-0

Lambin, P., Leijenaar, R. T. H., Deist, T. M., Peerlings, J., Jong, E. E. C. de, Timmeren, J. E. van, Sanduleanu, S., Larue, R. T. H. M., Even, A. J. G., Jochems, A., Wijk, Y. van, Woodruff, H. C., Soest, J. van, Lustberg, T., Roelofs, E., Elmpt, W. van, Dekker, A., Mottaghy, F. M., Wildberger, J. E., & Walsh, S. (2017). Radiomics: the bridge between medical imaging and personalized medicine [Review of *Radiomics: the bridge between medical imaging and personalized medicine*]. *Nature Reviews Clinical Oncology*, *14*(12), 749–762. Nature Portfolio. https://doi.org/10.1038/nrclinonc.2017.141

Latypov, T., So, M., Hung, P. S.-P., Tsai, P., Walker, M., Tohyama, S., Tawfik, M., Rudzicz, F., & Hodaie, M. (2023). Brain imaging signatures of neuropathic facial pain derived by artificial intelligence. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-37034-y

Leger, S., Zwanenburg, A., Pilz, K., Lohaus, F., Linge, A., Zöphel, K., Kotzerke, J., Schreiber, A., Tinhofer, I., Budach, V., Sak, A., Stuschke, M., Balermpas, P., Rödel, C., Ganswindt, U., Belka, C., Pigorsch, S., Combs, S. E., Mönnich, D., … Richter, C. (2017). A comparative study of machine learning methods for time-to-event survival data for radiomics risk modelling. *Scientific Reports*, *7*(1). https://doi.org/10.1038/s41598-017-13448-3

Liu, N., Liu, M., Tian, W., Zhai, Y., Lv, W., Wang, T., & Guo, S. (2024). The value of machine learning based on CT radiomics in the preoperative identification of peripheral nerve invasion in colorectal cancer: a two-center study. *Insights into Imaging*, *15*(1). https://doi.org/10.1186/s13244-024-01664-1

Liu, Z., Wang, S., Dong, D., Wei, J., Fang, C., Zhou, X., Sun, K., Li, L., Li, B., Wang, M., & Tian, J. (2019). The Applications of Radiomics in Precision Diagnosis and Treatment of Oncology: Opportunities and Challenges [Review of *The Applications of Radiomics in Precision Diagnosis and Treatment of Oncology: Opportunities and Challenges*]. *Theranostics*, *9*(5), 1303–1322. Ivyspring International Publisher. https://doi.org/10.7150/thno.30309

Llorián-Salvador, Ó., Akhgar, J., Pigorsch, S., Borm, K. J., Münch, S., Bernhardt, D., Rost, B., Andrade-Navarro, M. A., Combs, S. E., &

Peeken, J. C. (2023). The importance of planning CT-based imaging features for machine learning-based prediction of pain response. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-43768-6

Mes, S. W., Velden, F. H. P. van, Peltenburg, B., Peeters, C. F. W., Beest, D. E. te, Wiel, M. A. van de, Mekke, J. M., Mulder, D. C., Martens, R. M., Castelijns, J. A., Pameijer, F. A., Bree, R. de, Boellaard, R., Leemans, C. R., Brakenhoff, R. H., & Graaf, P. de. (2020). Outcome prediction of head and neck squamous cell carcinoma by MRI radiomic signatures. *European Radiology*, *30*(11), 6311–6321. https://doi.org/10.1007/s00330-020-06962-y

Naseri, H., Skamene, S., Tolba, M., Faye, M. D., Ramia, P., Khriguian, J., David, M., & Kildea, J. (2023). A Scalable Radiomics- and Natural Language Processing–Based Machine Learning Pipeline to Distinguish Between Painful and Painless Thoracic Spinal Bone Metastases: Retrospective Algorithm Development and Validation Study. *JMIR AI*, *2*. https://doi.org/10.2196/44779

Pai, S., Bontempi, D., Hadžić, I., Prudente, V., Sokač, M., Chaunzwa, T. L., Bernatz, S., Hosny, A., Mak, R. H., Birkbak, N. J., & Aerts, H. J. W. L. (2024). Foundation model for cancer imaging biomarkers. *Nature Machine Intelligence*, *6*(3), 354–367. https://doi.org/10.1038/s42256-024-00807-9

Park, J. E., Kim, H. S., Kim, D., Park, S. Y., Kim, J. Y., Cho, S. J., & Kim, J. H. (2020). A systematic review reporting quality of radiomics research in neuro-oncology: toward clinical utility and quality improvement using high-dimensional imaging features [Review of *A systematic review reporting quality of radiomics research in neuro-oncology: toward clinical utility and quality improvement using high-dimensional imaging features*]. *BMC Cancer*, *20*(1). BioMed Central. https://doi.org/10.1186/s12885-019-6504-5

Parmar, C., Großmann, P., Rietveld, D., Rietbergen, M. M., Lambin, P., & Aerts, H. J. W. L. (2015). Radiomic Machine-Learning Classifiers for Prognostic Biomarkers of Head and Neck Cancer. *Frontiers in Oncology*, *5*. https://doi.org/10.3389/fonc.2015.00272

Parmar, C., Leijenaar, R. T. H., Großmann, P., Velazquez, E. R., Bussink, J., Rietveld, D., Rietbergen, M. M., Haibe-Kains, B., Lambin, P., &

Aerts, H. J. W. L. (2015). Radiomic feature clusters and Prognostic Signatures specific for Lung and Head & Neck cancer. *Scientific Reports*, *5*(1). https://doi.org/10.1038/srep11044

Peng, Z., Wang, Y., Wang, Y., Jiang, S., Fan, R., Zhang, H., & Jiang, W. (2021). Application of radiomics and machine learning in head and neck cancers [Review of *Application of radiomics and machine learning in head and neck cancers*]. *International Journal of Biological Sciences*, *17*(2), 475–486. Ivyspring International Publisher. https://doi.org/10.7150/ijbs.55716

Pham, T. D., Teh, M., Chatzopoulou, D., Holmes, S., & Coulthard, P. (2024). Artificial Intelligence in Head and Neck Cancer: Innovations, Applications, and Future Directions. *Current Oncology*, *31*(9), 5255–5290. https://doi.org/10.3390/curroncol31090389

Piffer, S., Greto, D., Ubaldi, L., Mortilla, M., Ciccarone, A., Desideri, I., Genitori, L., Livi, L., Marrazzo, L., Pallotta, S., Retico, A., Sardi, I., & Talamonti, C. (2024). Radiomic- and dosiomic-based clustering development for radio-induced neurotoxicity in pediatric medulloblastoma. *Child s Nervous System*, *40*(8), 2301–2310. https://doi.org/10.1007/s00381-024-06416-6

Rudie, J. D., Rauschecker, A. M., Bryan, R. N., Davatzikos, C., & Mohan, S. (2019). Emerging Applications of Artificial Intelligence in Neuro-Oncology [Review of *Emerging Applications of Artificial Intelligence in Neuro-Oncology*]. *Radiology*, *290*(3), 607–618. Radiological Society of North America. https://doi.org/10.1148/radiol.2018181928

Salama, V., Godinich, B., Geng, Y., Humbert-Vidan, L., Maule, L., Wahid, K. A., Naser, M. A., He, R., Mohamed, A., Fuller, C. D., & Moreno, A. C. (2023). Artificial Intelligence and Machine Learning in Cancer Related Pain: A Systematic Review [Review of *Artificial Intelligence and Machine Learning in Cancer Related Pain: A Systematic Review*]. *medRxiv (Cold Spring Harbor Laboratory)*. Cold Spring Harbor Laboratory. https://doi.org/10.1101/2023.12.06.23299610

Salama, V., Humbert-Vidan, L., Godinich, B. M., Wahid, K. A., El-Habashy, D., Naser, M. A., He, R., Mohamed, A., Sahli, A., Hutcheson, K. A., Gunn, G. B., Rosenthal, D. I., Fuller, C. D., & Moreno, A. C. (2024).

Comparison of Machine Leaning Models for Prediction of Acute Pain Severity and On-Treatment Opioid Utilization in Oral Cavity and Oropharyngeal Cancer Patients Receiving Radiation Therapy: Exploratory Analysis from a Large-Scale Retrospective Cohort. *medRxiv (Cold Spring Harbor Laboratory)*. https://doi.org/10.1101/2024.02.06.24302341

Salama, V., Humbert-Vidan, L., Godinich, B., Wahid, K. A., El-Habashy, D., Naser, M. A., He, R., Mohamed, A., Sahli, A. J., Hutcheson, K. A., Gunn, G. B., Rosenthal, D. I., Fuller, C. D., & Moreno, A. C. (2025). Machine learning predicting acute pain and opioid dose in radiation treated oropharyngeal cancer patients. *Frontiers in Pain Research*, *6*, 1567632–1567632. https://doi.org/10.3389/fpain.2025.1567632

Sarac, K., & Güveniş, A. (2024). Using radiomics for predicting the HPV status of oropharyngeal tumors. *Journal of Engineering and Applied Science*, *71*(1). https://doi.org/10.1186/s44147-023-00355-w

Scapicchio, C., Gabelloni, M., Barucci, A., Cioni, D., Saba, L., & Neri, E. (2021). A deep look into radiomics [Review of *A deep look into radiomics*]. *La Radiologia Medica*, *126*(10), 1296–1311. Springer Science+Business Media. https://doi.org/10.1007/s11547-021-01389-x

Shahriari, A., Ahari, S. G., Mousavi, A., Sadeghi, M., Abbasi, M. R., Hosseinpour, M., Mir, A., Zanganeh, D. Z., Gharedaghi, H., Ezati, S., Sareminia, A., Seyedi, D., Shokouhfar, M., Darzi, A. M., Ghaedamini, A., Zamani, S., Khosravi, F., & Anar, M. A. (2025). Machine Learning–Driven radiomics on 18 F-FDG PET for glioma diagnosis: a systematic review and meta-analysis [Review of *Machine Learning–Driven radiomics on 18 F-FDG PET for glioma diagnosis: a systematic review and meta-analysis*]. *Cancer Imaging*, *25*(1). BioMed Central. https://doi.org/10.1186/s40644-025-00915-8

Sheikh, K., Lee, S. H., Cheng, Z., Lakshminarayanan, P., Peng, L., Han, P., McNutt, T., Quon, H., & Lee, J. (2019). Predicting acute radiation induced xerostomia in head and neck Cancer using MR and CT Radiomics of parotid and submandibular glands. *Radiation Oncology*, *14*(1). https://doi.org/10.118

6/s13014-019-1339-4

Shi, Y., Huang, Q., Lyu, J., Dong, T., & Sun, J. (2025). Progress of MRI-based radiomics and deep learning for predicting the prognosis of locally advanced rectal cancer (Review) [Review of *Progress of MRI-based radiomics and deep learning for predicting the prognosis of locally advanced rectal cancer (Review)*]. *Oncology Letters*, *30*(5), 1–13. Spandidos Publishing. https://doi.org/10.3892/ol.2025.15282

Shui, L., Ren, H., Yang, X., Li, J., Chen, Z., Cheng, Y., Zhu, H., & Shui, P. (2021). The Era of Radiogenomics in Precision Medicine: An Emerging Approach to Support Diagnosis, Treatment Decisions, and Prognostication in Oncology [Review of *The Era of Radiogenomics in Precision Medicine: An Emerging Approach to Support Diagnosis, Treatment Decisions, and Prognostication in Oncology*]. *Frontiers in Oncology*, *10*. Frontiers Media. https://doi.org/10.3389/fonc.2020.570465

Singh, G., Singh, A., Bae, J., Manjila, S., Spektor, V., Prasanna, P., & Lignelli, A. (2024). -New frontiers in domain-inspired radiomics and radiogenomics: increasing role of molecular diagnostics in CNS tumor classification and grading following WHO CNS-5 updates [Review of -*New frontiers in domain-inspired radiomics and radiogenomics: increasing role of molecular diagnostics in CNS tumor classification and grading following WHO CNS-5 updates*]. *Cancer Imaging*, *24*(1). BioMed Central. https://doi.org/10.1186/s40644-024-00769-6

Song, B., Yadav, I., Tsai, J., Khorrami, M., & Kann, B. H. (2025). Artificial Intelligence for Head and Neck Squamous Cell Carcinoma: From Diagnosis to Treatment. *American Society of Clinical Oncology Educational Book*, *45*(3). https://doi.org/10.1200/edbk-25-472464

Taha, H. A., Zeilani, R., Haddad, R. H., & Abdalrahim, M. S. (2025). Artificial intelligence and machine learning techniques for predicting neuropathic pain in patients with cancer: A systematic review. *Digital Health*, *11*. https://doi.org/10.1177/20552076251358315

Teng, X., Zhang, J., Zwanenburg, A., Sun, J., Huang, Y., Lam, S., Zhang, Y., Li, B., Zhou, T., Xiao, H., Liu, C., Li,

W., Han, X., Ma, Z., Li, T., & Cai, J. (2022). Building reliable radiomic models using image perturbation. *Scientific Reports*, *12*(1). https://doi.org/10.1038/s41598-022-14178-x

Timmeren, J. E. van, Cester, D., Tanadini-Lang, S., Alkadhi, H., & Baeßler, B. (2020). Radiomics in medical imaging—"how-to" guide and critical reflection [Review of *Radiomics in medical imaging—"how-to" guide and critical reflection*]. *Insights into Imaging*, *11*(1). Springer Nature. https://doi.org/10.1186/s13244-020-00887-2

Tortora, M., Gemini, L., Scaravilli, A., Ugga, L., Ponsiglione, A., Stanzione, A., D'Arco, F., D'Anna, G., & Cuocolo, R. (2023). Radiomics Applications in Head and Neck Tumor Imaging: A Narrative Review. *Cancers*, *15*(4), 1174–1174. https://doi.org/10.3390/cancers15041174

Ujjahan, S., Noman, A. S. M., Al-Johani, S. S., Shinwari, Z., Alaiya, A., & Islam, S. S. (2026). Deep learning and machine learning integration of radiomics and transcriptomics predicts response-adapted radiotherapy outcome and radiosensitivity in resectable locally advanced laryngeal carcinoma. *Frontiers in Artificial Intelligence*, *8*, 1738174–1738174. https://doi.org/10.3389/frai.2025.1738174

Vallières, M., Kay-Rivest, E., Perrin, L. J., Liem, X., Furstoss, C., Aerts, H. J. W. L., Khaouam, N., Nguyen-Tan, P. F., Wang, C.-S., Sultanem, K., Seuntjens, J., & Naqa, I. E. (2017). Radiomics strategies for risk assessment of tumour failure in head-and-neck cancer. *Scientific Reports*, *7*(1). https://doi.org/10.1038/s41598-017-10371-5

Wakabayashi, K., Koide, Y., Aoyama, T., Shimizu, H., Miyauchi, R., Tanaka, H., Tachibana, H., Nakamura, K., & Kodaira, T. (2021). A predictive model for pain response following radiotherapy for treatment of spinal metastases. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-92363-0

Wang, M., Perucho, J. A. U., Hu, Y., Choi, M. H., Han, L., Wong, E. M. F., Ho, G., Zhang, X., Ip, P. P. C., & Lee, E. (2022). Computed Tomographic Radiomics in Differentiating Histologic Subtypes of Epithelial Ovarian Carcinoma. *JAMA Network Open*, *5*(12). https://doi.org/10.1001/jamanetworkopen.2022.45141

Wishart, L. R., Ward, E. C., & Galloway, G. J. (2023). Advances in and applications of imaging and radiomics in head and neck cancer survivorship. *Current Opinion in Otolaryngology & Head & Neck Surgery*, *31*(6), 368–373. https://doi.org/10.1097/moo.0000000000000918

Wu, J., Qin, C., Zhou, Y., Wei, X., Qin, D., Chen, K., Cai, Y., Shen, L., Yang, J., Xu, D., Chai, S., & Xiong, N. (2024). Machine learning to predict radiomics models of classical trigeminal neuralgia response to percutaneous balloon compression treatment. *Frontiers in Neurology*, *15*. https://doi.org/10.3389/fneur.2024.1443124

Xiao, L., Bazyar, S., Ferris, M. J., Molitoris, J. K., Allor, E., Thomas, H., Arons, D., Schumaker, L. M., Krc, R., Mendes, W. S., Tran, P. T., Sawant, A., Mehra, R., Gaykalova, D. A., & Ren, L. (2025). Identification of CT based radiomic biomarkers for progression free survival in head and neck squamous cell carcinoma. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-85498-x

Xu, Y., Li, Y., Wang, D., Zhang, Y., & Huang, D. (2025). Addressing the current challenges in the clinical application of AI-based Radiomics for cancer imaging. *Frontiers in Medicine*, *12*. https://doi.org/10.3389/fmed.2025.1674397

Yolchuyeva, S., Giacomazzi, E., Tonneau, M., Lamaze, F., Orain, M., Coulombe, F., Malo, J., Belkaïd, W., Routy, B., Joubert, P., & Manem, V. (2023). Radiomics approaches to predict PD-L1 and PFS in advanced non-small cell lung patients treated with immunotherapy: a multi-institutional study. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-38076-y

Zhang, B., Lian, Z., Zhong, L., Zhang, X., Dong, Y., Chen, Q., Zhang, L., Mo, X., Huang, W., Yang, W., & Zhang, S. (2020). Machine-learning based MRI radiomics models for early detection of radiation-induced brain injury in nasopharyngeal carcinoma. *BMC Cancer*, *20*(1). https://doi.org/10.1186/s12885-020-06957-4

Zhang, Y., Wu, S., Zhou, M., Pan, H., Fan, Q., Xie, J., Xiao, X., Zhang, T., Shu, J., Luo, Y., Ma, D., & Yang, Q. (2025). Machine learning model for predicting neuropathic pain following thoracic oncology surgery. *Frontiers in Oncology*, *15*, 1725412–1725412. https://doi.org/10.3389/fonc.2025.1725412

Zheng, S., Cui, X., & Ye, Z. (2025). Integrating artificial intelligence into radiological cancer imaging: from diagnosis and treatment response to prognosis. *Cancer Biology and Medicine*, *22*(1), 6–13. https://doi.org/10.20892/j.issn.2095-3941.2024.0422