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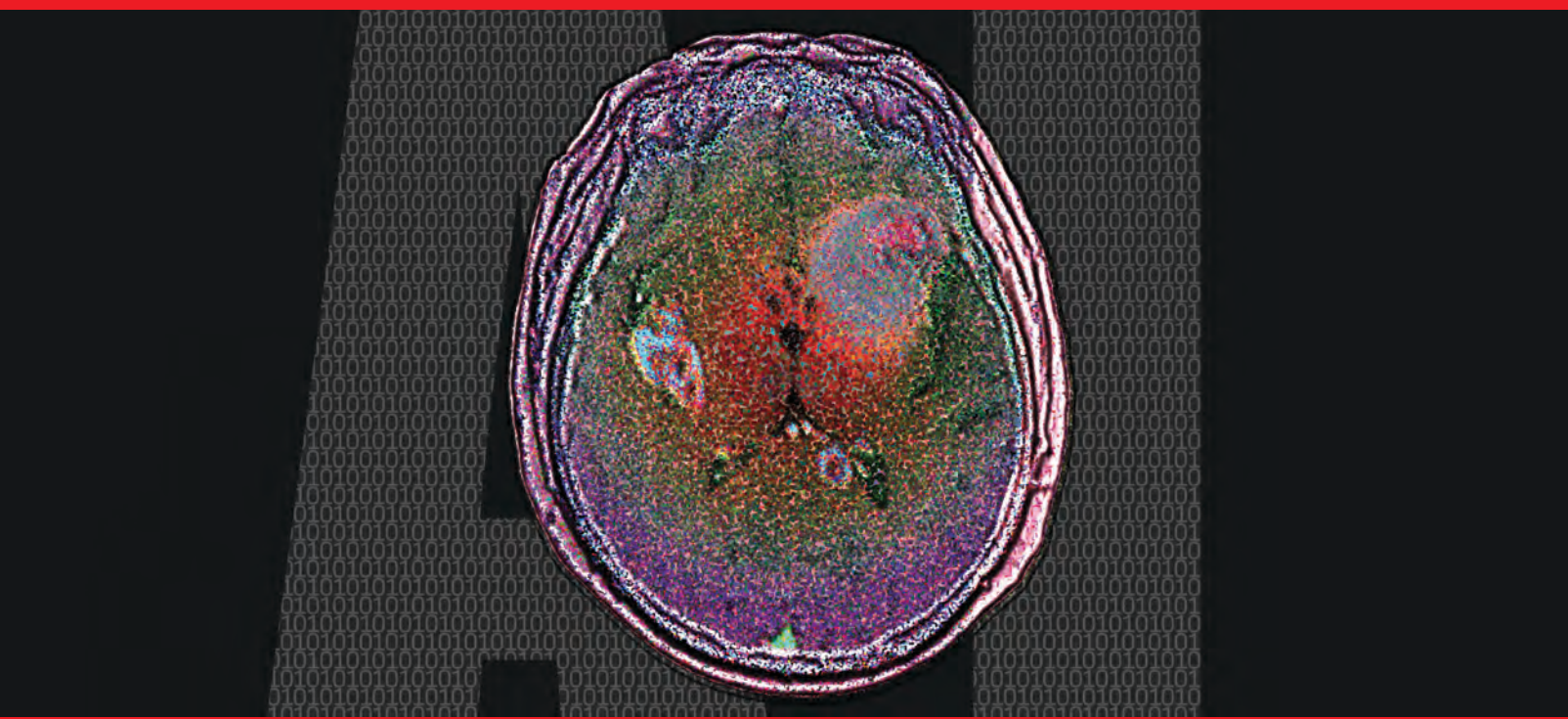

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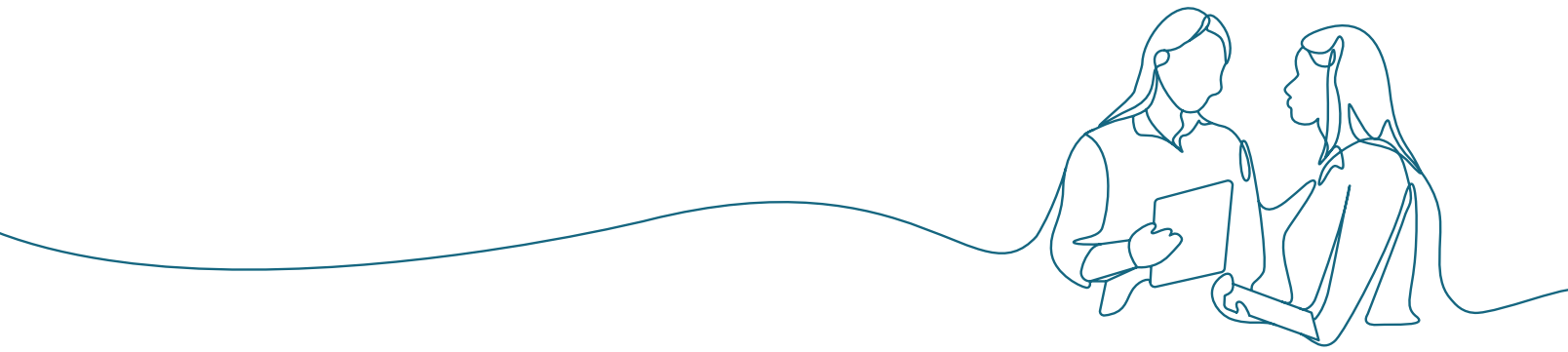

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Shine On: *ARO* Updates and Opportunities

John H. Suh, MD

Dr Suh is the editor-in-chief of *Applied Radiation Oncology*, and professor and chairman, Department of Radiation Oncology at the Taussig Cancer Institute, Rose Ella Burkhardt Brain Tumor and Neuro-Oncology Center, Cleveland Clinic, Cleveland, OH.

Happy summer! We hope this issue finds you enjoying the season's added daylight and perhaps a sunny getaway to relax and recharge. In line with bright horizons, we have a few updates and reminders we are excited to share, including the addition of two new members to the *ARO* editorial advisory board:

Vimoj J. Nair, MBBS, MD, MSc, FRCPC, is an associate professor of radiation oncology at the University of Ottawa; and a clinician investigator in the Clinical Epidemiology Program (CEP) at the Ottawa Hospital Research Institute (OHRI), Ontario, Canada. Dr. Nair will serve as the CNS section co-head of the *ARO* board.

Maria Tolia, MD, MSc, PhD, is an associate professor of radiation oncology, Faculty of Medicine, University of Crete, Greece, and head of the Radiation Oncology Department, University Hospital of Herakleion in Crete. She will head the gynecologic oncology section of our board.

We are very pleased to welcome Drs Nair and Tolia to *ARO* and appreciate the important insight they will also contribute as members of the international radiation oncology community.

ARO Opportunities

Additionally, we would like to remind you of the many offerings *ARO* produces beyond the pages of the journal. Please head to www.appliedradiationoncology.com for a closer look at:

Blogs. Featuring topics from climate change to redlining to brachytherapy's current reputation (and beyond), our regularly updated library of blogs provides engaging summaries on thought-provoking subjects.

Webinars. Complimentary and on demand, these 1-hour presentations take a deep dive into various radiation oncology topics, typically expanding on review articles published in the journal. Initial webinars are featured live with audience Q&As that round out the events.

Podcasts. Hosted currently by medical students pursuing radiation oncology, these engaging discussions explore pressing topics in areas such as education, adaptive radiation therapy, virtual reality, global health, terminology debates, and more.

Student committees. Along with developing podcasts and webinars, *ARO*'s self-regulated student committees offer opportunities in peer review, writing, and social media engagement, as well as a chance to network with fellow medical students.

Enewsletters. The Student Scan enewsletter is a wonderful quarterly resource written for students by students and presents interviews with radiation oncologists, synthesized hot topics, field opportunities, and more. *ARO* also features a biweekly enewsletter for subscribers, which highlights industry news and updates regarding journal activities.

Continuing education. Each issue features complimentary CE articles approved for 1 hour of credit, and a catalog of offerings is available online.

We hope you explore, share, and enjoy these opportunities, as well as the new articles that we are proud to feature in this quarter's issue. We wish you a safe, wonderful summer, and thank you very much for your continued support of *ARO*'s efforts in print and online!

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Integrating AI and Human Expertise: Exploring the Role of Radiomics in Multidisciplinary Tumor Boards

Description

This review article discusses the relationship between artificial intelligence (AI) and radiomics in oncology decision-making, exploring the fundamentals of AI-powered radiomics, its workflow, and the role of radiomic features. The article also describes the integration of AI in radiology, radiation oncology, and medical oncology, particularly its impact on multidisciplinary tumor board (MDT) decision-making, treatment planning, and predicting treatment responses, prognosis, and disease progression. Additional highlights include the role of machine learning algorithms and their impact on MDT decision-making, as well as challenges and implications of AI-driven radiomics in MDTs regarding ethical, financial, and regulatory aspects.

Learning Objectives

Upon completing this activity:

1. Clinicians will understand how AI-driven radiomics and advancements in oncology have the potential to personalize treatment, reduce diagnostic variability, and improve treatment plans.
2. Clinicians will be better prepared to enhance MDT decision-making by learning how radiomic analyses can help provide precise, quantitative data for noninvasive, tailored treatments, with combined radiogenomics enhancing predictive accuracy.

Authors

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Target Audience

1. Radiation oncologists
2. Related oncology professionals

Commercial Support

None

Accreditation/Designation Statement

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Integrating AI and Human Expertise: Exploring the Role of Radiomics in Multidisciplinary Tumor Boards

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Abstract

In the ever-evolving landscape of oncology, the integration of artificial intelligence (AI) with radiomics has transformed the decision-making processes within multidisciplinary tumor boards (MDTs). MDTs serve as forums where specialists collaboratively discuss and recommend comprehensive treatment plans for patients with cancer, considering various clinical perspectives. This narrative review explores the synergistic relationship between AI and radiomics in oncology decision-making. We discuss the fundamentals of AI-powered radiomics, its workflow, and the role of radiomic features. Moreover, we delve into the integration of AI in radiology, radiation oncology, and medical oncology, emphasizing its impact on MDT decision-making, treatment planning, and predicting treatment responses, prognosis, and disease progression. Furthermore, we highlight the role of machine learning algorithms and their impact on MDT decision-making. We discuss the challenges and future implications of AI-driven radiomics in MDTs, considering ethical, financial, and regulatory aspects. Finally, we emphasize the transformative potential of AI-powered radiomics in reshaping oncology decision-making, facilitating more personalized and effective treatment strategies within MDTs.

Keywords: radiomics, artificial intelligence, multidisciplinary tumor boards, algorithm processing, prognostication models, liquid biopsy, radiation oncology, innovation in oncology, patient-centered care, multidisciplinary team building

Introduction

In the ever-evolving field of oncology, the utilization of artificial intelligence (AI) with radiomics has paved an integral path of innovation, redefining decision-making processes toward novel precision within multidisciplinary tumor boards (MDTs). MDTs are forums where specialists collaborate to collectively discuss and recommend a comprehensive treatment plan for patients with cancer.[1] The collaborative nature of MDTs plays a key role in addressing the complexities of cancer care, considering various perspectives of clinical presentation, ranging from surgical oncology to medical and radiation oncology backed with radiological and pathological support.

Studies such as that by Kočo et al emphasize the significance of MDTs in improving diagnostic accuracy, treatment planning, and patient outcomes. Active discussions

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within MDTs allow for a holistic understanding of individual cases, considering not only the clinical aspects but also the unique clinical presentation of each patient, thereby offering an individualized approach for each patient.[2] As stated by Meng et al, incorporation of radiomics can be a key component of precision therapy and an innovative approach to the collective decision-making process in MDTs, resulting in more personalized and tailored treatment plans, avoidance of treatment delays due to invasive procedures, and reflecting a unique integration of diverse knowledge in enhancing patient-centric disease management.[3]

The background of the transformative shift of cancer care toward AI lies in the intrinsic challenges posed by conventional oncological approaches, which are marked by limitations in data processing speed, pattern recognition, and personalized insights. The combination of AI and radiomics, a field focused on extracting quantitative information from medical images, holds immense promise in addressing these challenges. Embracing AI-powered radiomics in oncology decision-making is evident in its ability to swiftly process vast and complex imaging datasets, facilitating an understanding of subtle patterns and variations within tumors.[4]

This narrative review aims to provide a comprehensive overview of the synergistic relationship between AI and radiomics in oncology. By delving into the background issues of traditional methodologies and interpreting the transformative potential offered by AI-driven radiomics, this communication seeks to bridge the gap between the theoretical insights and practical implications. Through a critical review of the current landscape, we aim to emphasize the significance of this combination in reshaping the decision-making processes in MDTs, discussing its challenges and, emphasizing the need for a paradigm shift toward AI-powered radiomic applications in multidisciplinary clinical practice.

Fundamentals of AI-Powered Radiomics

Understanding Radiomic Workflow in Oncology

Radiomics can be defined as the extraction of data from medical imaging and its practical application within the field of oncology with the intent to improve diagnosis, prognostication, and devising treatment recommendation within the MDT setting, with the goal of delivering timely precise treatment. The role of radiomics in oncology revolves around a spectrum of properties, ranging from shape, size, texture, and intensity to a comprehensive depiction of tumor heterogeneity. The rationale behind incorporating radiomics lies in the notion that subtle patterns within medical images may contain high-dimensional data about tumor biology, behavior, response to treatment, and prognosis, which, once utilized, can translate into transformative oncological patient care.[4]

Radiomic workflow is a collaborative effort involving radiologists, data scientists, and imaging experts. Its process involves tumor segmentation, preprocessing of acquired images, representative feature extraction, model development, and validation (**Figure 1**). Extracted features include signal intensity and spatial relationships among pixels within gross tumor volume (GTV), followed by validation of proposed data through a cross-check carried out on the dataset.[4]

In a landmark study by Lambin et al, radiomics was referred to as a bridge between medical imaging and personalized management, highlighting its potential to decipher the complexities of tumor biology.[5]

Radiomic Features

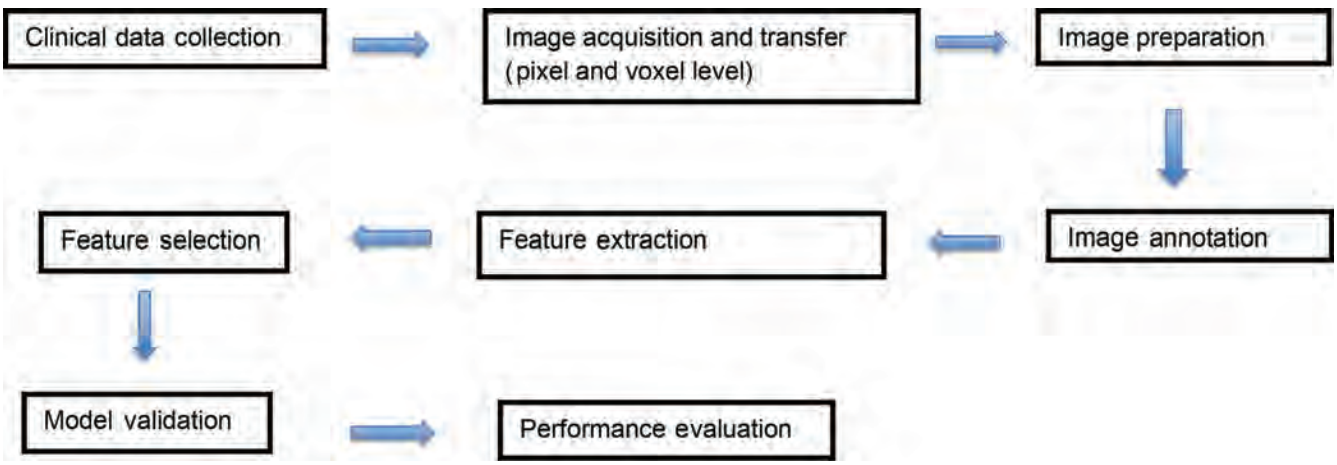
A study by Kocak et al provided a detailed algorithm highlighting the proficiency of AI algorithms in smoothly processing extensive imaging datasets, facilitating a rapid and comprehensive evaluation of radiomic features. Features such as data curation and preprocessing strategies such as pixel resampling using the Medical Image Processing, Analysis, and Visualization (MIPAV) software, and 3DSlicer, play an integral role in optimizing the extraction of quantitative information.[6]

Furthermore, machine learning and deep learning—two key concepts in radiomics—are the AI subfields revolutionizing medical diagnostics, treatment, and research. A machine learning process encompasses various techniques, such as decision trees (DTs), random forests (RFs), and support vector machines (SVMs), for classifying tumor types in medical imaging and neural networks, aiding in diagnosis and drug discovery by identifying various therapeutic targets.

Each model's practical application is grounded in an understanding of its strengths and practicality, with a few relevant practical scenarios listed as follows:

- *Decision trees*: These are ideal when interpretability is crucial, suitable for small- to medium-sized datasets, and useful for understanding feature importance. For instance, while combining DTs can yield valuable insights, the complexity increases and consensus varies depending on the specific criteria and number of DTs compared in the case of prostatic adenocarcinoma.[7]

Figure 1. Radiomic workflow diagram.



Radiomic workflow diagram detailing the process: beginning with data entry, followed by feature extraction, then proceeding to model validation, and concluding with the evaluation of the formulated model at each step in the Radiomics workflow.

- *Random forests*: These are effective for high-dimensional data, providing robustness and better generalization, and capable of handling larger datasets. For instance, risk prediction models via RFs in breast cancer prognosis and treatment have shown superior results in prediction accuracy compared with traditional regression models.[8]
- *Support vector machines*: These models are best for small- to medium-sized datasets, particularly for binary classification problems, and when there is a clear margin of separation between classes. For instance, SVM models have shown 90% accuracy, 80% sensitivity, and 80% specificity in the diagnosis of early prostate cancer.[9]
- *Neural networks*: These networks are suitable for large datasets and complex patterns, excelling in tasks involving image, audio, or text data, where deep learning can utilize vast amounts of data for feature learning and pattern recognition.

Deep learning, a subset of machine learning, focuses on deep neural networks. Examples are convolutional neural networks for detecting anomalies in x-rays, MRIs, and CT scans; recurrent neural networks for analyzing wearable device data to monitor patients' vitals; and deep reinforcement learning for optimizing personalized treatment plans. Traditional machine learning relies on manual feature engineering using simpler models that are suitable for smaller datasets and easier to interpret. It is particularly effective for structured data. In contrast, deep learning performs automatic feature extraction with more complex models that require large datasets and significant computational power. These models are harder to interpret and are often considered "black boxes," but are highly effective for unstructured and high-dimensional data.[10]

AI Integration in Radiology, Radiation Oncology, and Medical Oncology

AI can be defined as the simulation of human thinking, logical reasoning, problem solving, and deep learning processes by machines, particularly computers. AI in radiomics can be defined as advanced algorithms formulating predictions based on radiological data incorporated into the software. This integration of AI with radiomics may further amplify the recommended yield of MDT with the help of vast and complex datasets in oncology, the key revolution being in the field of neuro-oncology, where AI-incorporated radiomics and radiogenomic tools can potentially stratify various tumors based on radiological data only. This accelerated analysis can empower MDTs with information, enabling a thorough understanding of tumor characteristics and biology, which may not be readily apparent through conventional means, including biopsy for challenging locations. Examples include intracranial diffuse lesions (primary central nervous system lymphoma), or anatomically challenging regions (including malignancies involving the brain stem, or to differentiate between postradiation necrosis vs recurrence.[11]

AI applications regarding radiomics are not only limited to radiological image interpretation but also to their use in radiation oncology. They have facilitated the optimization of workflow, including

auto segmentation, auto contouring, dose optimization, radiation dose tracking, and automated quality assurance checks. However, prior to clinical implementation, a mandatory multidisciplinary evaluation of credibility preceded by the data entered is mandated. Therefore, AI, when combined with clinical decision support systems (CDSS), can greatly improve clinical and radiological workflows.[12]

Furthermore, systems such as RadCloud have standardized radiomic feature extraction and made it easier to integrate deep-learning-based image data from medical records in coherence with AI algorithms to incorporate into clinical research as well. A retrospective analysis of 139 patients done to predict breast tumors on mammograms and MRI images (built via RadCloud and designed to assess HER2/neu expression) predicted treatment response to targeted agents, including trastuzumab and pertuzumab, and estimated Ki-67 index. Another model utilized dynamic contrast-enhanced MRI to predict the probability of axillary lymph node metastasis in invasive ductal carcinoma of the breast. Likewise, a dataset of 165 patients with locally advanced rectal carcinoma was modeled to predict treatment response after neoadjuvant chemoradiation to guide subsequent treatment.[13]

In a multicenter study by Liu et al, MRI sequence data were integrated to predict pathological complete response to neoadjuvant therapy in patients with breast cancer. The study included radiological features of 586 patients, with a score involving features of 13,950 datasets. Quantitative analyses demonstrate it as a promising predictive tool for assessing tumor response in patients with locally advanced breast cancer, highlighting its potential and practical utility within MDTs.[14]

As AI continues to shape the medical imaging landscape, its integration into the field of urological oncology has led to impressive results. For prostate cancer diagnostics, machine learning has shown promise in refining clinically significant lesion detection, with some success in deciphering ambiguous lesions on multiparametric MRI (mpMRI). For kidney cancer, radiomics has emerged as a valuable tool for better distinguishing between benign and malignant renal masses and predicting tumor behavior from CT or MRI scans. Meanwhile, regarding bladder cancer, there is a burgeoning emphasis on the prediction of muscle invasive cancer and forecasting disease trajectory.[15]

Arimura et al discussed the concept of radiomics and its application in precision medicine in radiation therapy (RT), emphasizing the use of AI and machine learning algorithms to predict outcomes and toxicity for individual patients based on radiomic biomarkers extracted from medical images. It highlights the importance of radiomics in stratifying patients into subtypes based on imaging biomarkers to improve decision-making in precision medicine and treatment strategies, as well as the potential to avoid complications caused by invasive biopsies.[16]

The application of radiomics and machine learning in head and neck cancers has been further elaborated by Peng et al, emphasizing the extraction of quantitative imaging features to assess tumors and personalize diagnosis and treatment plans, with a focus on predicting prognosis indicators like progression-free survival, overall survival (OS), and distant metastasis. It also mentions the potential of radiomics in laying the foundation for personalized treatment and sequential treatment of tumors in otolaryngology patients.[17]

Abbasi et al highlight the promising association between radiological data and genetic factors and how the concept of virtual biopsies facilitated by radiomics may challenge traditional management, offering noninvasive tumor evaluation. The integration of radiomics and AI holds promise for personalized oncology, though data maturity remains a subject of ongoing exploration.[18]

The Role of Machine Learning Algorithms and Its Impact on MDT Decision-Making: Case Studies

Machine learning and deep learning algorithms play distinct, yet synergistic roles in the context of AI-driven radiomics. Machine learning processes involve the classification and categorization of radiomic features that help in ascertaining complex patterns of diagnostically challenging tumors. Cobo et al proposed guidelines for generalization and widespread application of radiomic features in the MDT setting, including metadata information availability, anonymization of patient demographics, and generalized availability of data to be reproduced and applied, along with the identification of potential bias, if any, during segmentation of radiomic features.[19]

How to handle metadata and its clinical application was described by Vial et al, who elaborated the role of deep learning via radiomics and its impact on cancer-specific predictive modeling, termed the *probabilistic max-pooling* technique, which has been shown to achieve excellent accuracy for numerous pattern recognition tasks for big image sets by reducing the amount of data to be analyzed and increasing efficiency for outcome prediction.[20] Chaddad et al addressed the fusion of deep learning and mpMRI to personalize the diagnosis and suggest risk stratification of prostate cancer compared with conventional transurethral resection

of the prostate.[21] The interplay of these algorithms into the radiomic workflow enhances the precision of tumor analyses, paving the way for more informed decision-making within an MTD setting.

The time required for a single patient to undergo full radiomic processing — including MRI DICOM prenormalization, tumor segmentation on multiple MRI sequences, radiomic feature extraction, and integration of radiomic and other clinical/molecular outputs into the selected model — can vary significantly, typically ranging from 3 to 8 hours. MRI DICOM prenormalization usually takes 15 minutes to 1 hour, depending on the need for manual adjustments. Tumor segmentation, which can be manual, semi-automatic, or automatic, generally requires 1 to 3 hours. Radiomic feature extraction often takes 30 minutes to 2 hours, influenced by the number and complexity of features extracted. Finally, integrating radiomic data with clinical and molecular outputs into the selected model usually needs 1 to 2 hours. The level of automation, quality of input data, operator experience, and computational resources significantly impact these time estimates.[22]

Table 1 highlights a few key studies incorporating radiomics and AI to enhance the workflow of MDT.

Radiation Therapy Treatment Planning and AI

One of the key breakthroughs lies in the optimization of treatment planning through the incorporation of radiomic features. Regarding radiation oncology, Shiradkar et al developed a computational framework known as radiomic-based TRaP for prostate cancer treatment planning based on MRI radiomic features. This framework comprises 3 distinct steps: radiomic feature-based detection of prostatic cancer on mpMRI data added via deep learning feature and segmentation; deformable co-registration of planning scan with diagnostic mpMRI for target and organ at risk of auto contouring; and radiomic-based planning for external-beam radiation therapy or brachytherapy. Their work showed that while maintaining normal target dose optimization objectives, radiomics-based planning minimizes the radiation dosage to the bladder and rectum.[26]

Treatment Response, Prognosis, and Disease Progression

Radiomics has been proven to be instrumental in predicting treatment responses. The identification of specific radiomic imaging biomarkers allows for the early assessment of a patient's likelihood of responding to therapy, enabling clinicians to customize treatment strategies.

Chan et al stratified early breast cancer patients into low-risk and high-risk for treatment failure in the analysis of 563 patients, utilizing the concept of Eigen tumors (a tool for feature selection). This concept involves image feature acquisition from pretreatment tumors and a predictive model of post-treatment response constructed using survival analysis showing a significant difference between estrogen receptor-positive and HER2/neu-negative tumors.[27] Such methods of quantification optimize MDTs by offering personalized insights for greater efficacy and targeted cancer treatment plans.

After studying tumor properties, AI-driven radiomic algorithms demonstrated superior capabilities in recognizing subtle patterns indicative of disease progression and metastasis.

Tang et al proposed a radiomic model for prognosis prediction in non-small cell lung cancer (NSCLC). This model integrates radiomic features derived from RT planning images with key clinical information, including age, gender, histology, and tumor stage. CT images of 422 patients with NSCLC were sourced from The Cancer Imaging Archive, with radiomic features extracted from the GTVs. Five learning algorithms were incorporated: DTs, RFs, extreme boost, SVMs, and generalized linear model. This combined radiomic model compared with the radiomic model predicted 1-year survival with greater accuracy of area under the curve (AUC) of 0.941, 0.856, and 0.949, respectively.[28]

Enhancing Collaborative Decision-Making in MDTs

Integrating Radiomics Into MDT Workflows

The introduction of radiomics into MDT workflows (**Figure 2**) has become a promising tool in the decision-making landscape. Radiomics adds a layer of precision to the collective understanding of tumor characteristics, providing a comprehensive analysis of medical images, extracting phenotypic features that reflect cancer prognosis. Along with radiomics, radiogenomics and radioimmunomics are other clinical data that can be incorporated to increase the predictive capacity and accuracy of MDT, but they warrant further research and generalization.[29]

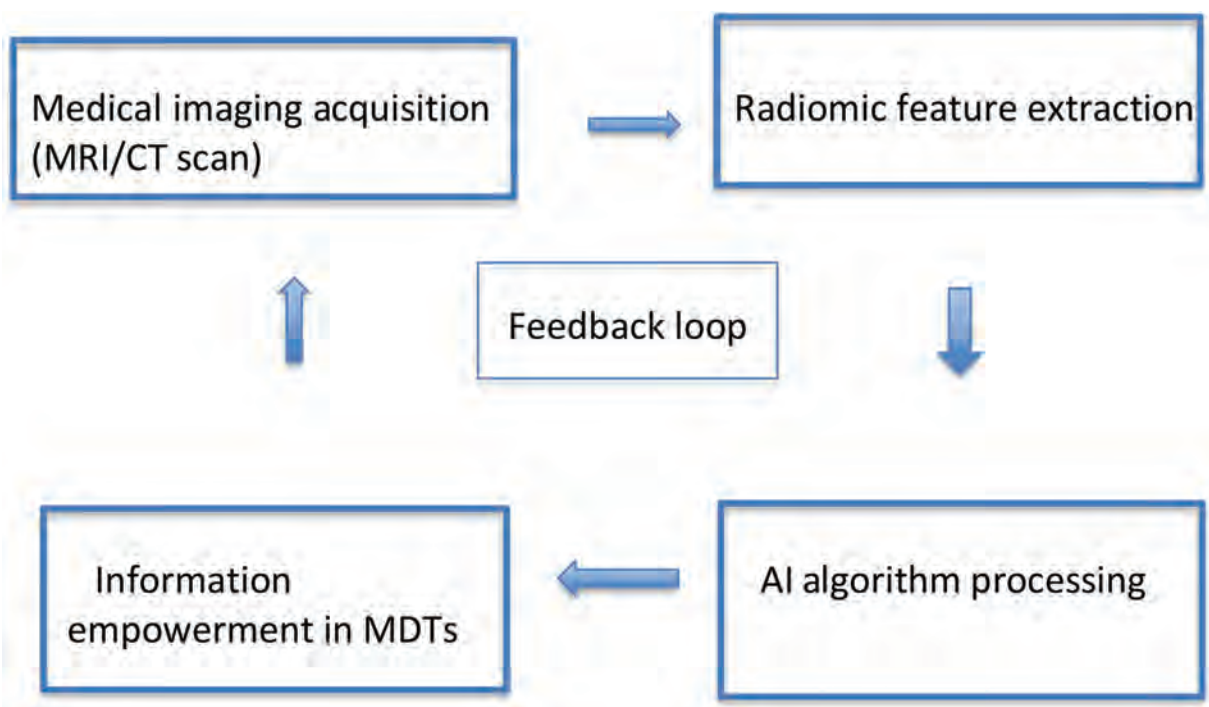
By seamlessly incorporating radiomic analyses into the MDT workflow, clinicians gain access to a source of quantitative data, augmenting their ability to tailor treatment strategies based on the unique radiomic profile of each patient's tumor in a noninvasive and individualized manner.[30]

Table 1. Key Studies Proposing Models for Incorporating AI and Radiomics in MDT Workflow

STUDY FOCUS	RESEARCH HYPOTHESIS	AI-DRIVEN RADIOMICS
Glioma radiomics[23]	Explores ai-based MRI radiomics for glioma classification and prognosis, emphasizing feature extraction and model construction	CNN, RNN, LSTM, VASARI radiomic features
Lung cancer radiomics[24]	Evaluates ai applications in lung cancer screening, diagnosis, and treatment, integrating imaging and clinical data	Multiview ConvNets, DLAD
Radiomics in predicting nodule (benign vs malignant)[25]	Investigates radiomics-based classification of malignant vs benign tumors	ICCs, Wilcoxon rank-sum test, ComBat harmonization, Lasso

Abbreviations: AI = artificial intelligence, CNN = convolutional neural network, RNN = recurrent neural network, LSTM = long short-term memory, VASARI = Visually AcceSAable Rembrandt Images, ConvNets = convolutional networks, DLAD = deep-learning-based automatic detection algorithm, ICCs = intraclass correlation coefficients, LASSO = least absolute shrinkage and selection operator.

Figure 2. The basic workflow of radiomic incorporation in multidisciplinary tumor boards (MDTs).



Proposed workflow of AI incorporation in MDT workflow.

AI Technology and Its Implication in the Real World: Applications

Radiomic features can be influenced by specific variations in images, impacting their ability to be widely applicable and reproducible. Moreover, the clinical utility of radiomics faces obstacles such as small study cohorts, insufficient external dataset validation, and inconsistent feature calculation methods. Despite these challenges, the integration of AI and radiomics holds immense promise in both clinical trials and real-world scenarios, with ongoing endeavors to mitigate these shortcomings. Key concerns include the lack of standardization and generalizability in radiomics findings, inadequate data quality control, issues with repeatability and reproducibility, imbalances in databases, and the risk of model overfitting. To

ensure robust and transferable results across different patient cohorts, radiomic procedures must meticulously address these pitfalls and challenges.

Fusco et al discussed the critical issues in radiomics research, emphasizing the need for high-quality images with consistent protocols, adequate and complete datasets, and distinct training and validation sets. They highlighted the problem of class imbalances and the necessity of reporting class-wise accuracy, sensitivity, and specificity.

Overfitting is a major concern when models include too many parameters, leading to the inclusion of irrelevant features and poor generalization. To prevent this, Fusco et al suggested using smoothing techniques and reducing input parameters, alongside validating models with separate datasets. They also mention the issue of underfitting, where overly simplistic models fail to classify data accurately, stressing the need for balanced model complexity.[31]

Another analysis involving advancements in AI-based radiomics for lung cancer immunotherapy deduced that current studies, while promising, were too preliminary and lacked methodological rigor, hindering clinical adoption. Most studies were observational rather than interventional and suggest further research with large cohorts, rigorous testing, validation, and methodological improvements to make these tools clinically viable for selecting patients with lung cancer for immunotherapy.[32]

AI and Analysis Before and After Its Advent in Oncology

AI and radiomics have demonstrated significant benefits in oncology, outperforming traditional methods and offering new opportunities for clinical decision support. For example, an AI model surpassed radiologists and conventional models in predicting lymph node metastasis in pancreatic ductal adenocarcinoma. Regarding radio-oncology, big data processing helps improve treatment outcomes and stimulates research on radiation responses, necessitating more AI training for medical physicists.[33] AI-based radiomics has enhanced clinical decision-making for patients with HCC (hepatocellular carcinoma)by improving prediction, diagnosis, and prognosis.[34] Machine learning tools for nodule management show promise in reducing radiology workload through automated detection, measurement, and risk stratification of nodules. Additionally, AI-based radiomics reduces interobserver variability in medical image interpretation, offering quantitative insights often overlooked by clinicians.

Peeken et al proposed incorporating AI into CDSS to facilitate precise, personalized treatment strategies and enhanced prognostication by analyzing extensive datasets to identify effective treatment patterns. This approach enables oncologists to make more informed decisions and provides patients with a deeper understanding of their disease and treatment options, empowering them throughout their care journey. Additionally, they emphasized that the role of AI is to support rather than dictate treatment decisions, underscoring the importance of comprehensive training for health care professionals to maintain patient-centered care. The future of cancer care is likely to involve a collaborative model that combines AI's capabilities with oncologists' expertise, promoting informed patient decisions and personalized treatment.[35] Moreover, AI's application in liquid biopsies can offer noninvasive insights into the genetic makeup of cancers, facilitating treatment monitoring and recurrence detection.[36]

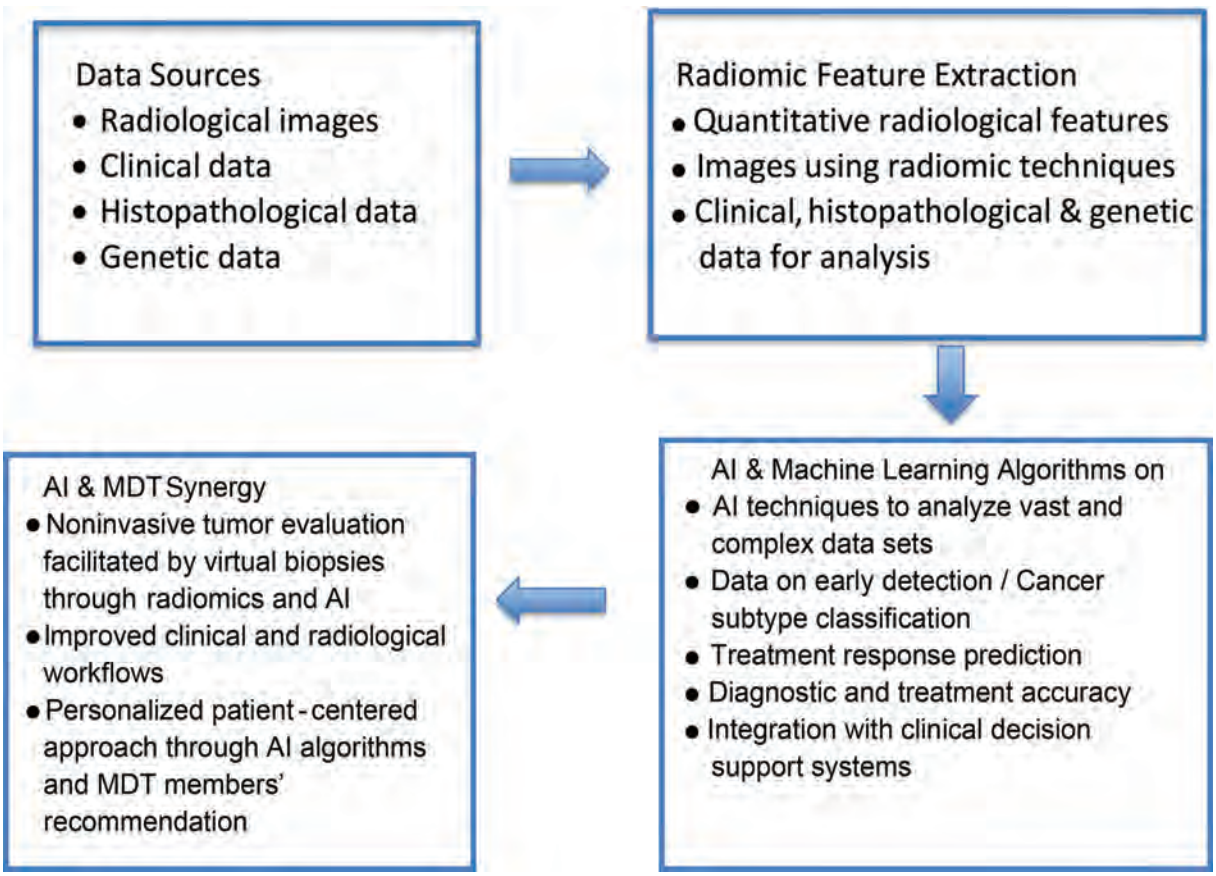
Such advancements suggest that AI and radiomics can revolutionize oncology care, making them more personalized, accurate, and efficient.[37]

Future Implications

In the realm of MDTs, the incorporation of AI-driven radiomics opens up novel opportunities for the future of precision oncology decision-making (see **Figure 3** for a proposed workflow of incorporating AI in MDTs). This drives a growing trend toward personalized treatment tactics, as evidenced by various studies demonstrating the ability to decode detailed radiomic processes and modify methods of treatment. Additionally, this advancement emphasizes the individualized nature of treatments, which adapt to the particular traits of each patient's tumor. Instantaneous combining of radiomic data enables MDTs to dynamically adjust to changing patient conditions, ensuring that treatment plans are continuously optimized. Meanwhile, a blend of multi-omics data, such as genomes, epigenetics, and radiomics, has been proven to provide a more in-depth evaluation of a patient's risk stratification and targeted treatment options in the era of immunotherapy.

Future implications of such a scenario can be seen in patients with IDH (isocitrate dehydrogenase)-wildtype glioblastoma, where the preoperative MRI features of 516 patients were extracted in coherence with molecular classifiers (MGMT methylation status). Patients were grouped into high risk and low risk on the basis of features backed up by SVMs. The basic difference between the two cohorts was the duration of OS. This trained radiomic model (SVM) was independently evaluated and a patient-wise OS

Figure 3. Proposed workflow of artificial intelligence (AI) incorporation in multidisciplinary tumor boards (MDTs).



Proposed workflow of artificial intelligence (AI) incorporation in multidisciplinary tumor boards (MDTs).

prediction was deduced. Multivariate models were generated first on the basis of clinical parameters, then by adding radiomic and molecular information. The evaluation of OS in the experimental cohort revealed AUCs of 0.78 (95% CI 0.70-0.85)/0.75 (95% CI 0.64-0.79) and 0.75 (95% CI 0.65-0.84)/0.63 (95% CI 0.52-0.71), respectively. Cox regression analysis showed a concordance index of 0.65 for clinical data compared with 0.75 for combined data (radiomics and molecular), thereby accurately predicting the OS. The authors mention that the key limitation of this study is the single-instituttion analysis of prospective data; hence, further collaboration and multi-institution analysis will strengthen SVM.[38]

Such developments hold potential for finding the gaps in current management, resulting in stronger decision-making. Addressing the interpretability challenge, these explainable AI models not only promote openness in decision-making processes but also build confidence among clinicians, which is imperative for collaborative decision-making in MDTs.

Unveiling the Other Perspective: Debate of Now

Ethical regulation of AI, particularly in the case of MDTs, is of paramount importance. For instance, the AI guiding physicians on the tumor board may lead to erroneous decisions influenced by AI. In such cases, accountability becomes a pressing question.

Given the novelty of these topics, their contribution to solving complex cases in patient management is of interest. However, there is a concern that they might also lead to misguided solutions since an oncologist or a radiologist has vast experience and can contemplate a scenario-based approach toward any recommendation for the patient's management. However, AI revolves around technical data only, with the individualized approach being a challenge; hence, creating a balance between dynamic power/knowledge will be a challenge.[39]

Exploring the financial aspect of AI utilization, particularly in diagnostics, presents intriguing possibilities. For instance, leveraging radiomics instead of biopsy could potentially reduce testing costs. But,

in contrast, it raises an important aspect regarding managing AI cost and reliability.[40]

Scenarios in which AI errors stem from false inputs result in inaccurate outputs raising important questions about responsibility and accountability. Moreover, current radiomic data are mostly retrospective image data, needing a centralized and robust technical support team.[41]

A proposed AI-integrated tumor board, along with its practical implementation, will involve several steps. Before the tumor board's meeting, the AI system processes all relevant patient data, including medical images, pathology reports, genetic profiles, and clinical histories, and generates detailed reports highlighting the key findings, potential diagnoses, and recommended treatment options. During the meeting, these AI-generated reports are reviewed by the multidisciplinary team, supplementing their expertise and leading to more informed and comprehensive discussions. The final treatment plan should be developed collaboratively, with the AI's recommendations serving as an additional resource to guide decision-making. The outcomes of the treatment plans will be monitored and fed back into the AI system to continuously improve its algorithms and recommendations.

Integrating AI into MTBs not only enhances diagnostic accuracy and streamlines decision-making but also personalizes treatment recommendations. While the processing and integration time required for radiomics and AI could initially pose a significant limitation in streamlining this concept, future advancements in methods and workflows hold promise for overcoming this challenge. Despite the current barriers, radiomics and AI have the potential to become invaluable tools in future tumor board settings. As methods become more refined and workflows optimized, the integration of radiomics and AI can enhance diagnostic accuracy, treatment planning, and patient outcomes in cancer care.

This collaborative approach, where AI aids rather than replaces human expertise, leverages the strengths of both technology and medical professionals to improve patient care outcomes. Fetah et al exemplify this integration, showcasing the practical benefits and potential of AI in a clinical setting, ultimately leading to timely interventions, more effective treatments, and improved outcomes for patients with cancer.[40]

Finally, ethical considerations, integration challenges, regulatory settings, economic elements, patient-centric beliefs, and long-term implications all highlight the need for continued research. By overcoming obstacles in these and related areas, the future prospects of AI-powered radiomics in MDTs can help advance precision oncology. This growth, in turn, can facilitate equitable and efficient implementation across the global health care arena, as MDTs serve as crucial forums for comprehensive collaborative decision-making, significantly impacting patient care and outcomes, and serving as a lifeline for patient management.[41]

Conclusion

The combination of radiomics and AI represents a revolutionary synergy that changes the oncology decision-making environment. This review delved into the intricate realms of AI-driven radiomics, elucidating their substantial impact on MDTs while also identifying the key challenges in solely relying on AI within the MDT context. When combined with AI algorithms' cognitive amplification powers, radiomics incorporation into MDT workflows allows for a quantum leap in our knowledge of and approach to cancer management.

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Dose Painting With the Gamma Knife Lightning Dose Optimizer: Technical Description and Validation of Dose Delivery

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Abstract

Objective: The recently introduced Gamma Knife (GK) Lightning (Elekta) fast inverse planning dose optimizer allows concurrent optimization of multiple targets, but the optimizer's use for generating a simultaneous integrated boost (SIB) plan has not been described and validated for accuracy of dose delivery. Here, we describe a method for creating an SIB using the GK Lightning optimizer and conduct validation of dose delivery.

Materials and Methods: Radiochromic film was positioned in an anthropomorphic phantom. A 15.7-cm^3 irregular contour was drawn to represent a brain metastasis resection cavity, a uniform 2-mm radial-expansion contour created, and a 1.6-cm^3 contour drawn representing a nodule of residual disease within the cavity. Targets were prescribed 3 Gy (2-mm expansion), 4 Gy (cavity), and 5 Gy (residual disease) in 1 fraction. Within the GammaPlan Lightning optimizer, "beam-on time" and "low-dose" settings were iteratively adjusted to create a clinically acceptable plan. Treatment was delivered using the GK Icon system. The film was scanned and calibrated for absolute dosimetry. Global gamma index analyses were performed at various dose and distance tolerances.

Results: An 18-minute treatment plan with 40 shots was delivered. Prescription isodose lines were 3 Gy at 55% (2-mm expansion), 4 Gy at 69% (resection cavity), and 5 Gy at 75% (residual disease). All target volumes had greater than or equal to 99% prescription dose coverage and the maximum dose was 6.9 Gy. Paddick conformality indices were 0.79 (2-mm expansion), 0.74 (resection cavity), and 0.15 (residual disease). Gamma index pass rate, mean, and median values were 77%, 0.68, and 0.54 at 1%/1-mm tolerance, 85%, 0.58, and 0.49 at 2%/1-mm tolerance, and 97%, 0.34, and 0.28 at 2%/2-mm tolerance.

Conclusion: We successfully created an SIB plan with the GK Lightning optimizer, verifying dose delivery within clinically acceptable tolerances. Future work is needed to determine optimal dose levels for use in clinical practice and determine what disease entities may benefit from an SIB.

Keywords: stereotactic radiosurgery, stereotactic radiation therapy, simultaneous integrated boost, SIB, fast inverse planning

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Introduction

Postoperative radiation therapy is strongly recommended for patients with resected brain metastases (BM).[1] Radiographic evidence of residual or recurrent disease is detected in 4% to 13% of patients with resected BM, including in 5% of patients following gross total resection.[2-5] Such patients may benefit from a simultaneous integrated boost (SIB) to areas of gross disease to improve local control,[6] while respecting brain dose-volume tolerances for radiosurgery.

As previous versions of the Gamma Knife (GK) (Elekta) treatment planning system did not explicitly allow for an SIB, Grossberg et al[7] described 2 methods of dose painting an SIB. These planning techniques rely on manual forward planning of nested targets, require significant user expertise, are limited to 2 dose levels, do not allow concurrent calculation of dosimetric coverage statistics for the nested treatment volumes, and have not undergone quality assurance for dose delivery validation. Validation of accurate dose delivery is particularly important given the complexity of overlapping dose calculation matrices.[8-10]

Recently, a fast inverse planning (FIP) dose optimizer (Lightning) was introduced for GK, allowing concurrent optimization of multiple targets while incorporating organs-at-risk (OAR) dose constraints.[11] This FIP optimizer demonstrated the potential to improve treatment planning quality and efficiency for a variety of clinical scenarios, showing particular utility when treating irregularly shaped targets.[12-15] Here, we describe the use of the Lightning FIP optimizer for dose painting in GK radiosurgery, using the example of residual or recurrent tumor at the time of adjuvant radiation therapy for a resected BM, and we conduct quality assurance of dose delivery. To demonstrate the accessibility and flexibility of this SIB technique, we extend the 2-target example of Grossberg et al[7] (resection cavity and gross tumor) by adding a third nested target consisting of a resection cavity radial margin.[16]

Materials and Methods

Technical Description of Dose Painting Technique

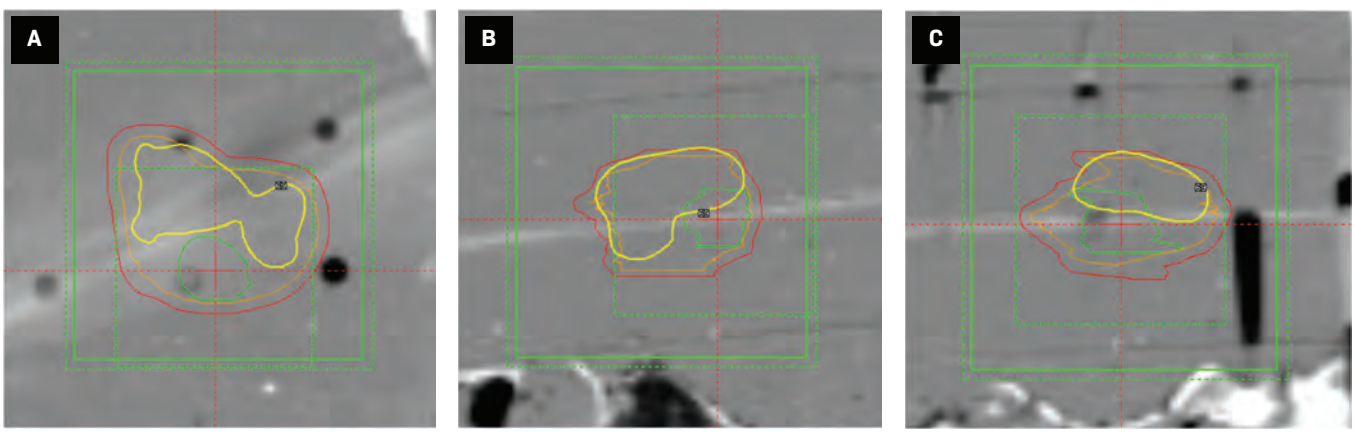
Standard GK techniques are used for patient setup, image co-registration, and target contouring. At least 2 nested target volumes are created consisting of the resection cavity and/or a radial expansion to a resection cavity margin, plus a volume capturing recurrent or residual gross tumor. Overlapping dose calculation matrices are placed for the nested targets. A prescription dose (in Gy) is specified for each target volume. If desired, a maximum dose can be specified and the option of "full coverage" can be selected to increase target coverage from the default of greater than or equal to 95% to greater than or equal to 99%. The OAR dose constraints can be specified but are not required. An initial plan is then optimized, typically using the default "low dose" (LD) and "beam-on time" (BOT) penalty settings of 0.50 (range, 0.00–1.00).

The initial plan is reviewed for metrics such as target coverage, total treatment time, Paddick conformity index (PCI), gradient index (GI), normal tissue dosimetry, and isodose. While the Lightning FIP does not allow the user to prescribe a specific isodose, the optimized isodose can be manipulated in subsequent iterations by changing the LD and BOT penalty settings, toggling the option of "full coverage," and/or providing values for "maximum dose." Treatment plan optimization is iterated under a variety of settings until a clinically acceptable plan is developed, at which point treatment delivery follows standard GK techniques.

Quality Assurance of Dose Delivery

To conduct quality assurance of this technique, we created a clinically representative treatment plan for an anthropomorphic phantom. Using a CT simulation scan of the phantom, a 15.7-cm^3 irregular contour was drawn to represent a brain metastasis resection cavity of a recently treated patient. A 2-mm uniform radial expansion was created for an additional contour (25.5 cm^3). A 1.6-cm^3 contour was drawn within the resection cavity to represent a gross tumor nodule. In GammaPlan software v11.3.1, overlapping dose matrices were placed using default positions (**Figure 1**). The 3 targets were prescribed 3 Gy (2-mm expansion), 4 Gy (resection cavity), and 5 Gy (gross tumor) in a single fraction. Prescription doses were selected to match the radiochromic film's optimal dose range, while approximating fractional doses used in 5-fraction treatments. Within the FIP optimizer, "full coverage" was selected, no maximum dose or OAR constraints were specified, and LD and BOT penalty settings were iteratively adjusted to create a clinically acceptable plan. On the GK Icon system, a custom occipital mold was made, an unexposed film (Gafchromic RTQA2) placed in the axial plane of the phantom's cranium, cone-beam CT (CBCT) co-registration conducted, and treatment delivered. The film was scanned (Epson Expression 11000XL) and calibrated for absolute dosimetry using a calibration curve generated from a 6-MV linear

Figure 1. Axial (A), coronal (B), and sagittal (C) views of a simultaneous integrated boost Gamma Knife treatment plan for an anthropomorphic phantom with 3 nested target contours (red = 2-mm margin, orange = resection cavity, green = gross tumor). Three overlapping dose calculation matrices are shown by green boxes (alternating dotted and solid lines). Radiochromic film is visualized as a white streak and is localized by the red reticule. The 4 Gy isodose line (yellow contour) results from the 27 shots planned to the resection cavity target and does not represent the composite 4 Gy isodose line of the total 40-shot plan (**Figure 2A**).



accelerator. Corrections were not made for dose delivered by CBCT.[17] To evaluate treatment accuracy, global gamma index analyses were performed at various dose and distance tolerances, excluding points below 30% of the maximum dose. The passing rate was defined as the percentage of points with gamma index less than 1. Film dosimetry and analysis were performed using Radiochromic.com software v4.0.[18]

Results

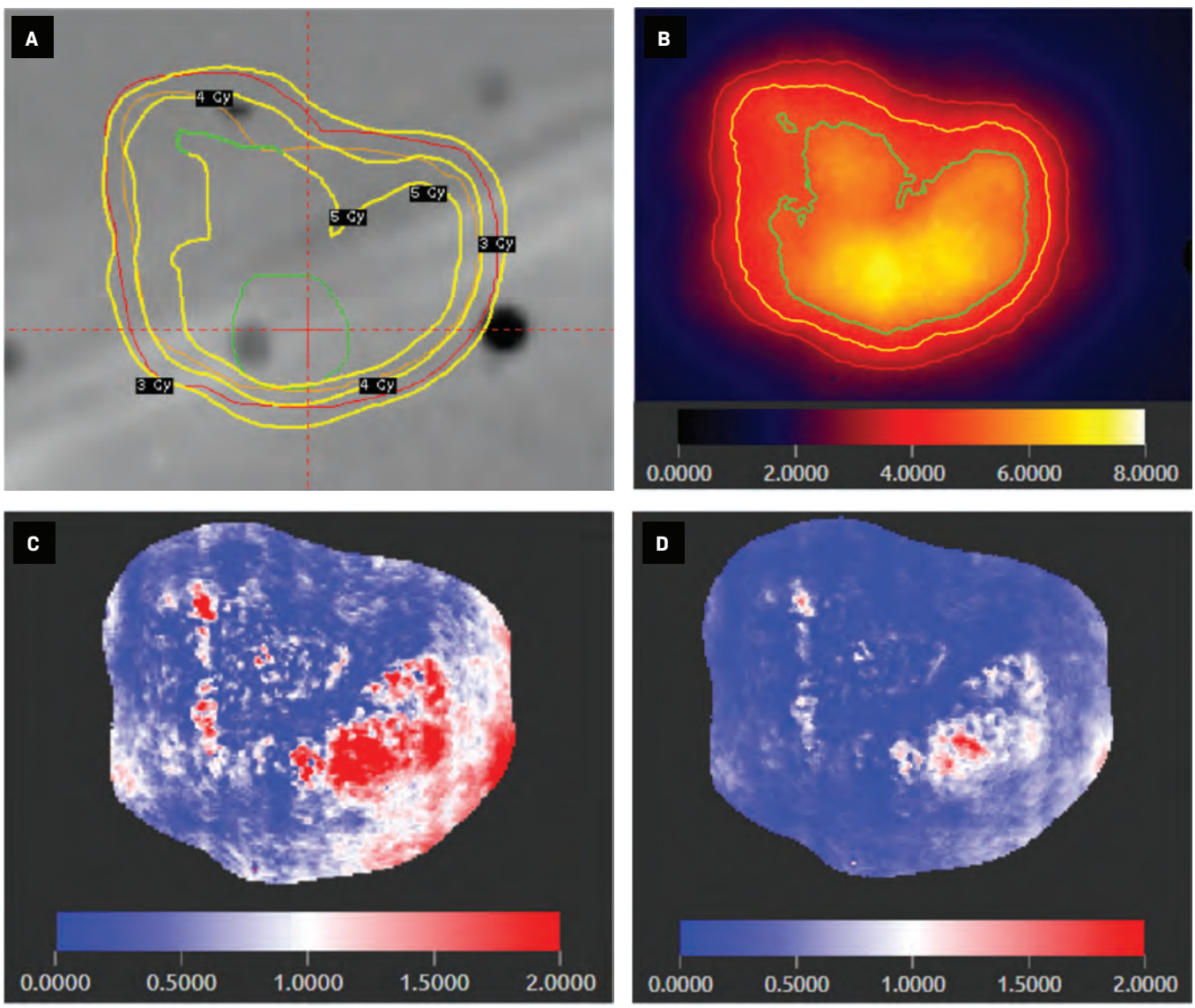
Using LD and BOT penalty settings of 0.60 and 0.90, respectively, an 18-minute treatment plan with 40 shots was created after 221 seconds of optimization. The plan included 7 shots to the 2-mm margin (2.01 min of BOT), 27 to the resection cavity (12.63 min), and 6 to gross tumor (3.14 min) (**Figure 3**). Prescription isodose lines were 3 Gy at 55% (2-mm expansion), 4 Gy at 69% (resection cavity), and 5 Gy at 75% (gross tumor) (**Figure 2A**). All target volumes had greater than or equal to 99% prescription dose coverage and the maximum dose was 7.0 Gy. Mean doses were 4.8 Gy (2-mm expansion), 5.2 Gy (resection cavity), and 6.1 Gy (gross tumor). PCI values were 0.79 (2-mm expansion), 0.74 (resection cavity), and 0.15 (gross tumor). GI was only available for the resection cavity (value = 2.5). On absolute dosimetry with Gafchromic film, the measured maximum dose was 7.112 Gy, 1.6% higher than planned. Gamma index pass rate, mean, and median values were 77%, 0.68, and 0.54 at 1%/1-mm tolerance, 85%, 0.58, and 0.49 at 2%/1-mm tolerance, and 97%, 0.34, and 0.28 at 2%/2-mm tolerance (**Figure 2**). An average of 17,883 points were evaluated per gamma index analysis.

Discussion

We demonstrated a method for conducting an SIB using the GK Lightning optimizer and validated dose delivery within acceptable clinical thresholds.[8,19] This method allows for concurrent optimization of multiple nested dose volumes, provides dosimetric statistics for each volume, and does not require significant user experience. Additionally, this technique can be applied to concurrently treat multiple brain lesions with an SIB. However, as the GammaPlan user interface is not optimized for SIB planning, this method may be prone to interpretive error. This is exemplified by the nonintuitive interpretation of individual isodose lines when looking at a single target volume (**Figures 1, 3**), as well as the lack of a color gradient for prescription isodose lines within a composite treatment plan (**Figure 2A**). Additionally, since shots are delivered sequentially on a target-by-target basis (**Figure 3**), and the total dose delivered to a given voxel is the summation of dose sequentially delivered to multiple targets (**Figure 2A**), this method may result in heterogeneous dose rate variability with an undetermined radiobiological significance and be more sensitive to intrafraction positioning errors.[20]

Clinically, our demonstration used the example of recurrent or residual tumor at the time of adjuvant radiation therapy for BM. This work does not address the optimal number of nested treatment volumes, the necessity of treating a radial

Figure 2. Axial view of simultaneous integrated boost Gamma Knife (Elekta) treatment plan for an anthropomorphic phantom (A) showing 3 target contours (red = 2-mm margin, orange = resection cavity, green = gross tumor) and isodose lines of 3 prescription doses (yellow contours: 3 Gy, 4 Gy, and 5 Gy). Radiochromic film of the delivered treatment plan calibrated for absolute dosimetry (B) with isodose lines of 3 prescription doses (red = 3 Gy, yellow = 4 Gy, green = 5 Gy) and color-scale legend of absolute dose (Gy). Gamma index analyses of radiochromic film at 1%/1-mm (C) and 2%/2-mm (D) tolerances with color-scale legend showing gamma index values (values <1 represent a passing score for a given point).

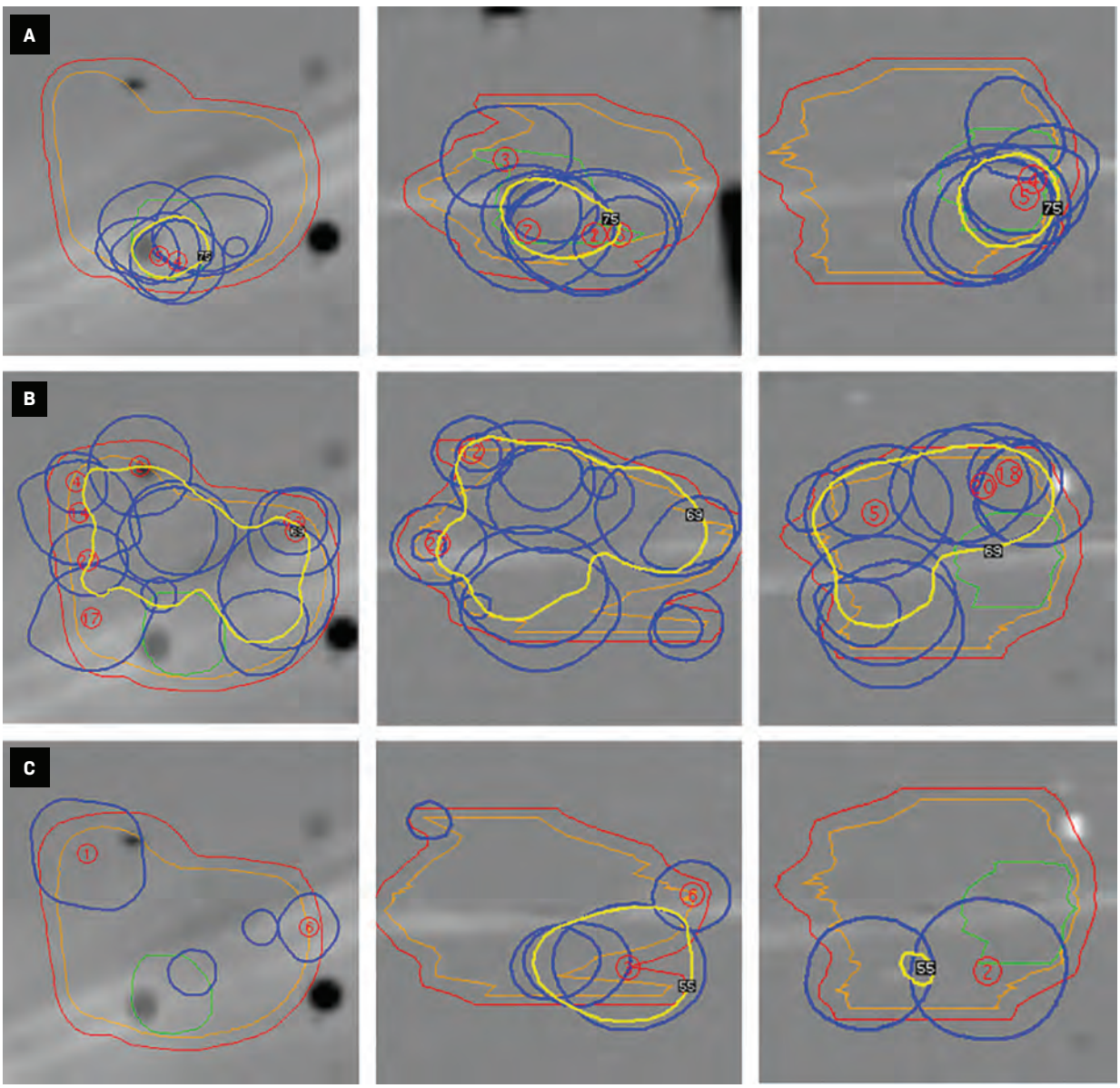


margin, nor does this work define the most appropriate dose levels or fractionation pattern.[21-24] For the treatment of BM, it is not well defined if an SIB improves outcomes or reduces toxicity, but this SIB method allows for standardization of treatment technique in future clinical trials designed to improve the therapeutic ratio of adjuvant stereotactic radiation therapy.[25] The application of this SIB technique is not limited to adjuvant BM therapy as it could be used to deliver internal boosts to primary brain tumors via lattice radiation therapy.[26,27] Prospective work is needed to optimize the clinical application of this technique to elucidate appropriate clinical indications and dose levels.

Conclusions

We successfully created an SIB plan with the GK Lightning optimizer and verified dose delivery within clinically acceptable tolerances. Future work is needed to determine optimal dose levels for use in clinical practice and what disease entities may benefit from an intracranial SIB.

Figure 3. Axial, coronal, and sagittal views (arranged from left to right) of Gamma Knife (Elekta) shot position for the gross tumor (A), resection cavity (B), and 2-mm expansion (C) target volumes. The yellow contour represents the prescription isodose line for each target (2-mm expansion = 3 Gy, resection cavity = 4 Gy, gross tumor = 5 Gy) resulting from the contribution of shots planned to the given target, as opposed to the total 40-shot plan (**Figure 2A**).



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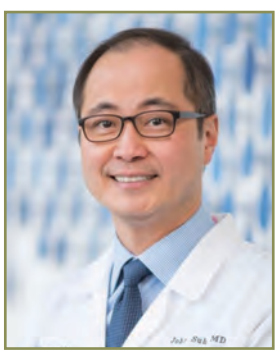

John Suh, MD, FASTRO, FACR

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Radiation-Induced Optic Neuropathy Following Radiation Therapy for a Recurrent Tuberculum Sellae Meningioma: A Case Report

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Abstract

A 62-year-old woman underwent a second surgery for a WHO grade 1 tuberculum sellae meningioma 4 years after her primary resection. The meningioma affected her right optic nerve, and there was a microscopic residual tumor after the second surgery. Due to the history of recurrence, residual tumor, and visual decline, she was offered postoperative radiation therapy of 1.8 Gy in 29 fractions, with a total dose of 52.2 Gy. Maximum doses to the anterior optic pathway structures were 53.7 Gy to the chiasm, 53.3 Gy to the right optic nerve, and 52.3 Gy to the left optic nerve. Following a transient improvement, her vision rapidly worsened 7 to 8 months later, with only finger counting possible in her left eye and a nearly total visual field loss. Visual acuity was reduced to 20/60 in the right eye, the visual field was reduced (especially in the lower 2 quadrants), and radiation-induced optic neuropathy (RION) was suspected. A rare yet disabling condition that may occur following radiation therapy, RION usually presents with painless, rapid visual deterioration in 1 or both eyes. Treatment options are limited, rendering this a devastating radiotherapeutic complication. Systemic steroids were administered to the patient without visual improvement. Bevacizumab was given as a last effort and, after 3 courses, MRI showed some improvement, with regression of presumed inflammatory changes in both optic nerves. However, the patient's visual function further deteriorated bilaterally. Three additional bevacizumab courses had no effect, neither visually nor radiographically. This case illustrates that despite precautions, including using doses considered relatively safe when planning radiation therapy, RION might develop and may have devastating consequences. Mitigating treatment options are limited.

Keywords: radiation-induced optic neuropathy, radiation therapy, visual impairment, meningioma, bevacizumab, case report

Case Summary

A formerly healthy 62-year-old woman experienced visual impairment in her right eye. MRI detected a tuberculum sellae mass, which was surgically removed with a presumed gross total resection. Histopathological examination showed a central nervous system (CNS) WHO grade 1 meningioma. Visual function

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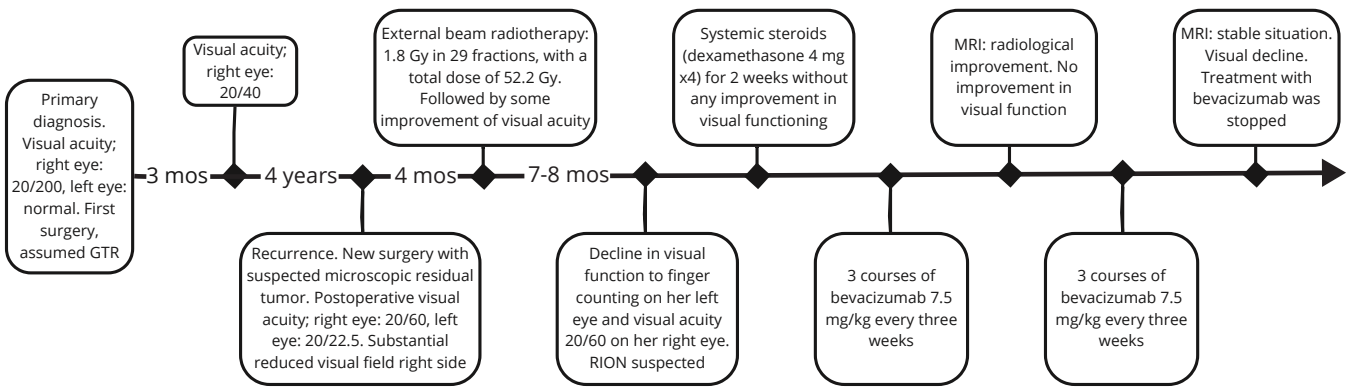
Figure 1. Timeline illustrating the patient's symptoms and treatment history. GTR, gross total resection; mos, months; RION, radiation-induced optic neuropathy.



improved following surgery. Four years later, the patient had progressive visual field loss and reduced vision in her right eye. A meningioma recurrence was detected and a re-resection was performed with microscopic residual tumor. Postoperative photon radiation therapy was administered 4 months later. Because of her already affected vision, a cautious fractionation of 1.8 Gy in 29 fractions, with a total dose of 52.2 Gy, was chosen. Unfortunately, her vision rapidly deteriorated 7 to 8 months later bilaterally. Radiation-induced optic neuropathy (RION) was suspected based on the clinical situation and radiological findings. Steroids, followed by bevacizumab, were administered without any clinical improvement, leaving the patient with substantial visual loss (**Figure 1** shows the timeline).

Imaging Findings

MRI showed a tuberculum sellae mass measuring 18 × 22 × 15 mm compressing the right optic nerve, suspicious of a meningioma (**Figure 2A-C**). The tumor was surgically removed using a pterional approach, with a presumed gross total resection as evaluated by the surgeon and shown in the postoperative MRI.

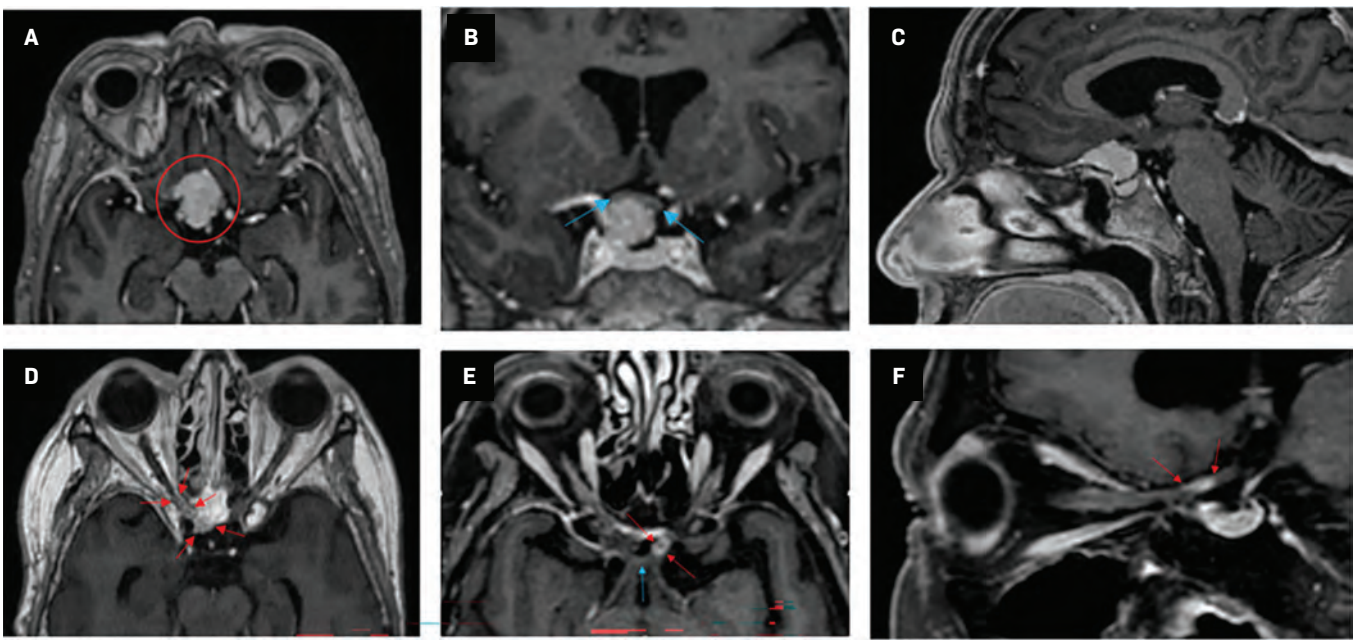
Four years following the first surgery, a tumor recurrence was detected, and MRI suggested that the tumor had grown into the optic canal. A new surgical procedure was performed, and postoperative MRI showed no evident residual tumor. However, the neurosurgeon suspected remaining microscopic tumor tissue in the optic canal. MRI taken as part of radiation therapy planning showed changes compatible with residual tumor alongside the right planum sphenoidale (**Figure 2D**). MRI taken 7 to 8 months following radiation therapy showed contrast enhancement suggestive of inflammatory changes affecting the right optic nerve and surprisingly also showed similar changes in the left optic nerve (**Figure 2E, Figure 2F**).

Diagnosis

Prior to the first surgery, the patient experienced progressive visual loss, resulting in a visual acuity of 20/200 in her right eye, and visual field loss in the temporally and lower 2 quadrants. Her vision was described as normal in the left eye prior to surgery. Visual function improved after surgery, and after 3 months visual acuity in the patient's right eye was assessed to be 20/40. Despite the successful initial surgery, a tumor recurrence was detected 4 years later. At this time point, the patient had reduced vision and a progressive visual field loss in her right eye. After the second surgery, her visual acuity was 20/60 in her right eye and 20/22.5 in the left eye. The right visual field was substantially reduced, especially in the lower 2 quadrants.

Based on recurrent disease, high probability of microscopic residual tumor remnants, and progressive loss of visual function, the patient was offered postoperative radiation therapy delivered with photons. Radiation therapy was administered 4 months following the last surgical procedure, and a conservative fractionation of 1.8 Gy in 29 fractions, with a total dose of 52.2 Gy, was chosen to keep anterior visual pathway doses below what is considered safe (**Table 1**) according to the European Particle Therapy Network Consensus. These standards recommend doses below 55 Gy to 0.03 cm^3 ($D_{0.03cc}$) to the chiasm and the optic nerves.[1] For the chiasm, the maximum dose (D_{max}) was 53.7 Gy and the mean dose (D_{mean}) was 51.7 Gy. The right optic nerve had a D_{max} of 53.3 Gy and a D_{mean} of 48.8 Gy, whereas the left optic nerve

Figure 2. Axial T1 sequence MRIs with contrast enhancement. (A-C) MRI prior to the first tumor resection. (A) The tumor (red circle) was 18 × 22 × 15 mm in its largest dimension and was at the frontal base of the skull with a slight preponderance to the right. (B) Blue arrows indicate proximity to the chiasm. (D) MRI taken as part of radiation therapy planning. There was a sparse residual tumor (red arrows) alongside the right planum sphenoidale and in the optic canal. (E,F) MRI approximately 9 months following completion of radiation therapy. Left optic nerve contrast enhancement (red arrows) is shown in proximity to the chiasm (blue arrow).



had a D_{max} of 52.3 Gy and a D_{mean} of 30.5 Gy. Radiation therapy dose distribution is shown in **Figure 3**. After radiation therapy, the patient reported minor improvement in visual function. Unfortunately, 7 to 8 months later her visual function again deteriorated over only a few weeks. Both eyes were affected, and deterioration was most pronounced in her left eye, with only finger counting possible and nearly total visual field loss. In the right eye, visual acuity was 20/60, with a substantially reduced visual field, especially in the lower 2 quadrants.

RION is primarily a diagnosis of exclusion, with tumor recurrence being the most important differential diagnosis. Tumor progression often results in a slower course of visual loss than RION.[2] The patient's vision loss was painless and rapid in onset, and radiological findings were bilateral and not consistent with neoplastic progression. Although MRI findings are nonspecific in RION-affected patients, neuro-ophthalmological examinations and clinical course/timing pointed to RION as the most likely cause of the patient's visual loss. Systemic steroids in high doses were administered for 2 weeks before gradual tapering off, without any improvement in visual function. As a last effort to improve visual function, it was decided to try bevacizumab 7.5 mg/kg every 3 weeks. Treatment was well tolerated, with no reported side effects. Evaluation with MRI after 3 courses showed some radiological improvement, with regression of presumed inflammatory changes affecting the right as well as the left optic nerve. Unfortunately, visual function testing by the ophthalmologist did not improve. Based on MRI findings, it was decided to try another 3 bevacizumab courses, hoping that improvement in vision function would follow with time. The radiological evaluation following the 3 previous bevacizumab courses was stable, whereas the patient's visual function continued to decline and bevacizumab treatment was discontinued.

Less than 1 year after radiation therapy, the patient's vision was reduced to finger counting. She had total visual field loss in her left eye and substantial visual field loss in her right eye, with only visual field remnants temporally. Examination revealed large bilateral optic disc retinal nerve fiber layer deficits. Unfortunately, no other treatment options were available and further efforts were focused on trying to improve quality of life with available visual aids.

Discussion

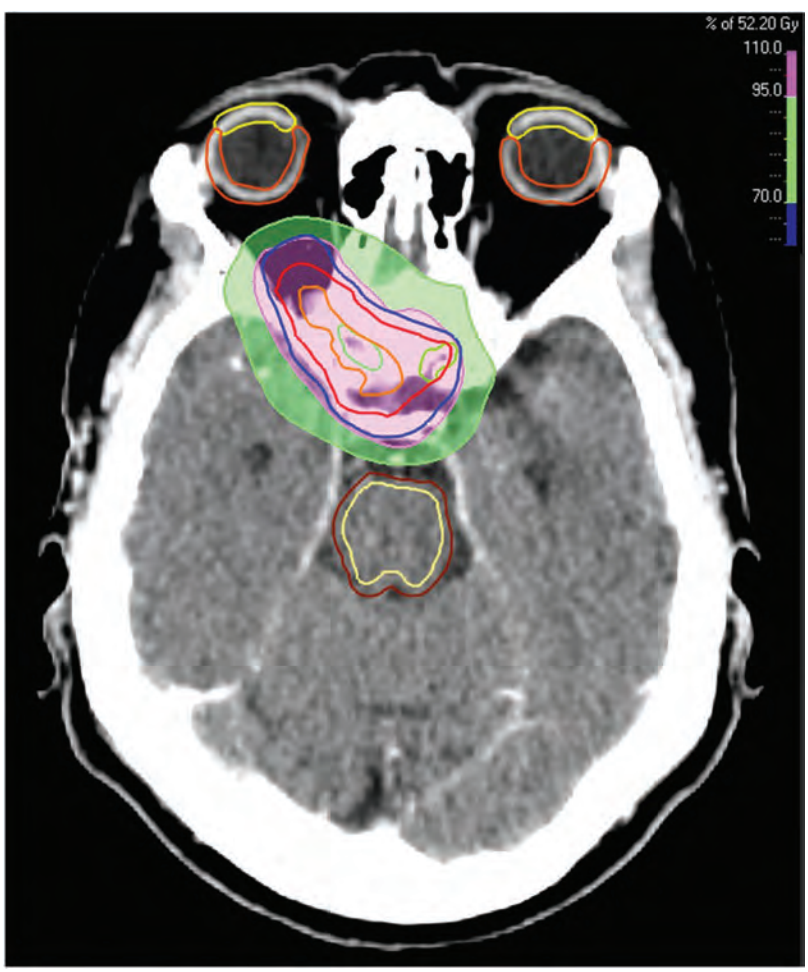
RION is a devastating, albeit rare, complication following radiation therapy and may leave patients

Table 1. Doses to the Anterior Visual Pathway

ORGAN	D_{MAX} (Gy)	D_{MAX} EQD2 (α/β = 2 Gy) (Gy)	D_{MEAN} (Gy)	D_{MEAN} EQD2 (α/β = 2 Gy) (Gy)	DOSE CONSTRAINTS (EQD2) AS RECOMMENDED BY QUANTEC
Optic chiasm	53.7	51.0	51.7	49.1	$D_{max} \leq 55$ Gy
Optic nerve, right	53.3	50.6	48.8	46.3	$D_{max} \leq 55$ Gy
Optic nerve, left	52.3	49.7	30.5	29.0	$D_{max} \leq 55$ Gy

Key: α/β= alpha/beta; D_{max}= maximum dose; D_{mean}= mean dose; EQD2 = equivalent dose in 2 Gy fractions; QUANTEC = Quantitative Analyses of Normal Tissue Effects in the Clinic.

Figure 3. The patient's radiation therapy plan, displaying dosage levels of 70% (green area) and 95% (pink area) of 52.2 Gy. Target volumes: orange line (gross tumor volume), red line (clinical target volume), and blue line (planning target volume). Organs at risk: green (optic nerves), yellow (cornea), orange (retina), dark brown (brainstem), and light yellow (brainstem core).



with considerable vision loss. It usually presents with subacute, profound, painless, and progressive visual loss. Symptoms typically appear between 10 and 20 months following radiation therapy, with previous data supporting a range from 3 months to 9 years from radiation therapy.[2-4] Data suggest that one-third of patients develop bilateral RION either simultaneously or sequentially.[4] Here, the patient received postoperative radiation therapy based on recurrence and microscopic residual tumor after resection. Although conservative dosing was used, RION evolved bilaterally.

The exact pathogenetic mechanism of RION is unknown. Possible contributing factors are vascular endothelial damage as a result of free radicals from irradiation,[5] neuroglial cell progenitors contributing to cellular damage, demyelination, and neuronal degeneration,[2,6] and obstruction of the arteries supplying the optic nerves and chiasm, resulting in optic atrophy.[4] Suggested risk factors for developing RION, based primarily on retrospective studies, include high cumulative radiation therapy doses, age (> 60), gender (female), vascular comorbidities, diabetes mellitus, smoking, chemotherapy, previous radiation therapy, pre-existing compression of optic nerves or chiasm by tumor, as well as repeated surgeries.[2,4,7] For RION to develop following fractionated radiation therapy, cumulative doses normally have to exceed 50 Gy in EQD2 (equivalent dose in 2 Gy fractions). Increased dose per fraction seems to be more important than cumulative doses, and latency may also be shorter with higher fractionation doses.[2,8]

Guidelines from the Quantitative Analyses of Normal Tissue Effects in the Clinic (QUANTEC) recommend a maximum dose (D_{max}) ≤ 55 Gy to the anterior optic apparatus, in fraction doses of ≤ 1.9 Gy. According to QUANTEC, RION was unusual for D_{max} < 55 Gy, with an increased risk (absolute risk 3%-7%) for D_{max} 55-60 Gy.[3] Parsons et al found that among optic nerves that received doses of ≥ 60 Gy, the 15-year actuarial risk of RION was 11% when the fraction dose was ≤ 1.9 Gy compared with 47% when the fraction dose was ≥ 1.9 Gy.[9] Nonetheless, because of uncertainties in calculating doses to anterior visual pathways and individual patient factors, RION should always be considered in patients who develop visual impairment following visual pathway radiation therapy, even if the doses delivered were considered safe.[2] Here, the patient is an example of the latter, and she also had some potential risk factors, including female gender, age above 60 years, and vision disturbances prior to radiation probably related to neoplastic compression of the anterior optic apparatus. She did not have hypertension, diabetes, or hyperlipidemia, never received chemotherapy, and was a nonsmoker.

Different treatment strategies for RION such as systemic corticosteroids, hyperbaric oxygen, and anticoagulation have shown little effect.[2,4,10] Bevacizumab is a recombinant humanized monoclonal antibody targeting vascular endothelial growth factor and has resulted in improvement in some patients with RION, although there is little evidence supporting its effectiveness.[8,11] Interestingly, here the patient had a radiological response after 3 courses of bevacizumab treatment, although her vision continued to deteriorate, leaving her with substantial visual loss. In hindsight, one may argue that the patient would have been much better off with a follow-up MRI and ophthalmologist examinations instead of radiation therapy. On the other hand, RION is an extremely rare complication after radiation therapy delivered with the fractionated regimen chosen for this particular patient. Importantly, for many patients, radiation therapy may prevent further vision deterioration caused by growing meningioma in the optic pathways.[12]

Conclusion

Radiation-induced optic neuropathy is a rare yet devastating condition following radiation therapy, leaving some patients with substantial visual loss, sometimes bilaterally. Awareness of recommended dose limits to anterior visual pathways and other potential risk factors is important to consider when planning radiation therapy. Even if the doses to optic nerves and the chiasm are below what is considered safe, RION may develop, and it is important to be aware of this during follow-up of patients treated with radiation therapy. Unfortunately, limited treatment options to mitigate RION are available. Further endeavors are needed to identify the risk factors for RION and improve treatment options.

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Portal Vein Stenosis Following Neoadjuvant Therapy With MRgART and Surgery for Pancreatic Cancer: A Case Report

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Abstract

Portal vein stenosis (PVS) is a rare but potentially devastating complication arising after definitive treatment of pancreatic cancer. The condition can manifest as symptomatic ascites, abdominal pain, splenomegaly, thrombocytopenia, as well as hemorrhage secondary to gastric or esophageal varices. The etiology is often multifactorial but has been associated with tumor progression, chemotherapy, vascular surgery, and radiation. We present a case in which a man with borderline-resectable pancreatic cancer developed symptomatic ascites secondary to PVS following treatment with neoadjuvant chemotherapy and subsequent 5-fraction MRI-guided adaptive radiation therapy and pancreaticoduodenectomy with vascular reconstruction. Though the incidence of PVS after ablative radiation therapy and surgery for pancreatic cancer appears to be low, it may be under-reported, and patients should be closely monitored in the setting of re-irradiation or planned vascular reconstruction. These findings may help inform future radiation therapy treatment planning guidelines to avoid excessive dose to the portal vein.

Keywords: portal vein stenosis, pancreatic cancer, MRI-guided adaptive radiation therapy, complication of radiation therapy, case report

Case Summary

A 63-year-old man with a past medical history of alcohol use disorder, recurrent pancreatitis, and colon cancer after sigmoidectomy and no adjuvant therapies presented to the emergency department for pancreatitis with obstructive jaundice. The patient was treated with a biliary stent, and CT showed a 4.0 × 3.8-cm mass located in the pancreatic head with greater than 180° involvement of the superior mesenteric vein (SMV). Endoscopic biopsy confirmed pancreatic adenocarcinoma. The patient was staged as clinical T2N1M0, stage IIB, and the tumor was deemed borderline-resectable after multidisciplinary tumor board review. The patient subsequently underwent 8 cycles of neoadjuvant FOLFIRINOX (fluorouracil, irinotecan, and oxaliplatin), followed by MRI-guided adaptive radiation therapy (MRgART) to 50 Gy in 5 fractions, with the SMV receiving a Dmax of 56.4 Gy (**Figure 1**). His CA19-9 level decreased from 766 U/mL to 51.8 U/mL, and SMV involvement was less than 180°, making him eligible for pancreatoduodenectomy (PD) with planned en bloc SMV resection with venovenous anastomosis (International Study Group type 3). At 104 days postsurgery and 150 days postradiation, the patient developed symptomatic ascites and CT imaging demonstrated severe

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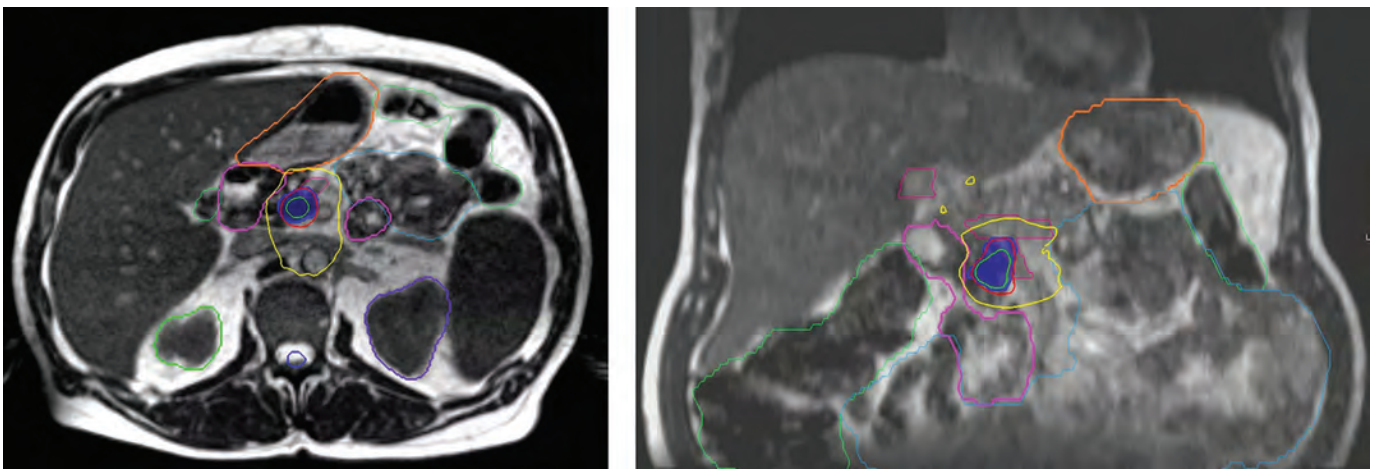
Figure 1. MRIdian (ViewRay) treatment plan of simultaneous modulated accelerated radiation therapy dosimetry. Dark blue color wash is the 50 Gy optimization (Opti) structure to gross disease with adaptive dose painting to target and avoid luminal organs at risk with step-and-shoot intensity-modulated radiation therapy. Adjacent portal vein/superior mesenteric vein is contoured in magenta. Other pertinent OARs for adaptive recontouring include stomach (orange), duodenum (pink), small bowel (cyan), and large bowel (green); 110%, 100%, and 60% isodose lines are displayed.



stenosis of the SMV at the confluence with the main portal vein (PV). He underwent paracentesis, and 860 mL of ascitic fluid was removed; cytology was negative. Portal venography demonstrated portal vein stenosis (PVS) at the SMV orifice and occlusion of the splenic vein at the confluence with the main PV. Angioplasty of the PVS was performed and resolved the patient's symptomatic ascites. The patient also experienced variceal bleeding, requiring endoscopic clipping and eventually embolization, and remains in clinical surveillance for pancreatic cancer without evidence of recurrent disease.

Imaging

MRI performed as part of the initial diagnostic workup characterized the tumor as a 3.8-cm mass at the pancreatic head, along with a left 1.3-cm periaortic node suspected to be inflammatory. There was vascular encasement of the portosplenic confluence by the tumor as well as greater than 180° contact with the SMV. After neoadjuvant therapy, CT imaging revealed that the pancreatic mass had decreased to 2.6 cm, and there was a decrease in vascular involvement and patent PV (**Figure 2A**). Postsurgical CT showed small-volume ascites, along with narrowing of the PV, SMV, and splenic vein with peripancreatic edema (**Figure 2B**). In surveillance, CT showed increasing ascites and ultrasound showed stenosis at the PV-SMV confluence (**Figure 2C**). The patient underwent paracentesis, and CT demonstrated persistent narrowing of the portal venous confluence. Transhepatic portal venography demonstrated stenosis of the main PV at the SMV orifice and chronic occlusion of the splenic vein at the confluence with the main PV (**Figure 3**). A timeline of the imaging findings is shown in **Table 1**.

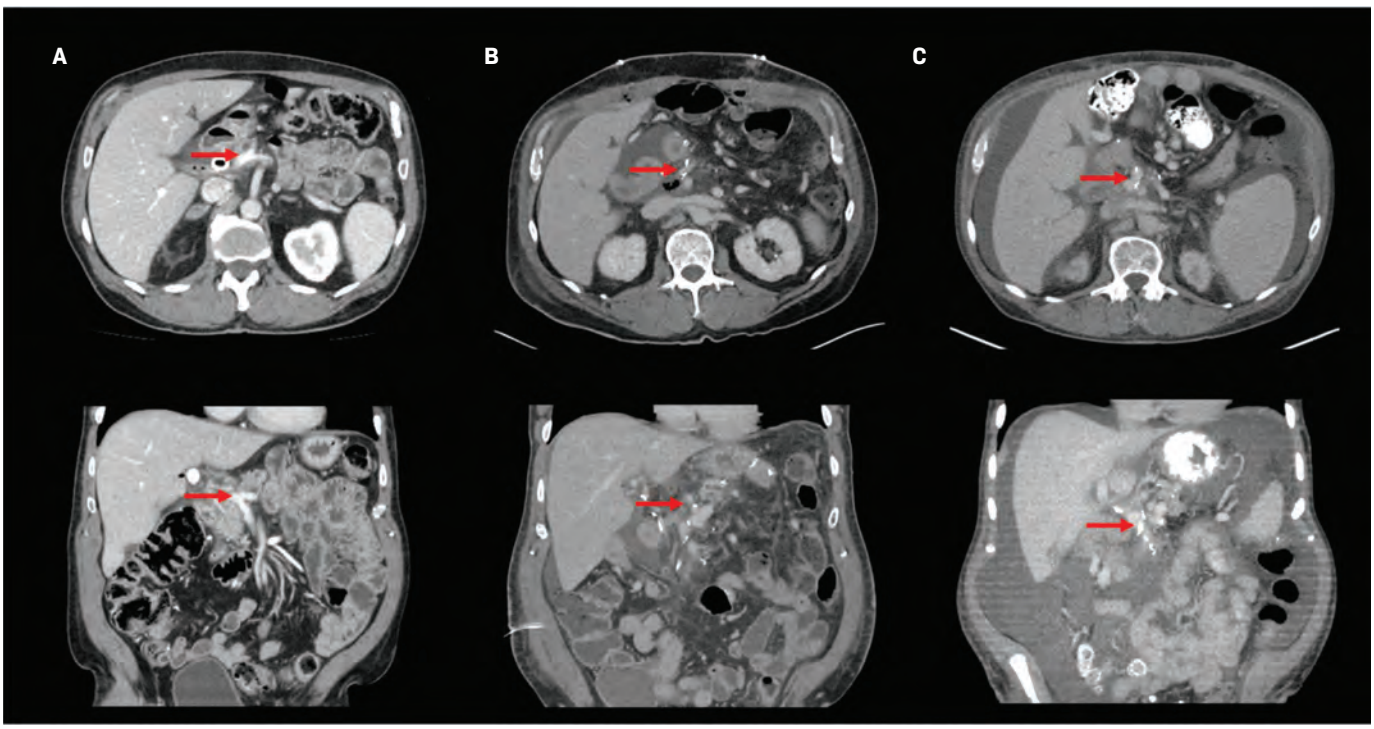
Diagnosis

The diagnosis was consistent with symptomatic PVS secondary to occlusion of the splenic vein at the confluence with the main PV, as demonstrated by the imaging that followed the patient's surgery as well as the evaluation by an interventional radiologist who performed portal venography. The patient only became symptomatic with ascites and esophageal varices after imaging findings began to show PVS. He had no prior history of varices, ascites, or liver failure despite a history of alcohol abuse. Additionally, the imaging taken early in his treatment course showed no evidence of PVS.

Discussion

Here, we describe a case report of symptomatic PVS in a patient with adenocarcinoma of the pancreas treated with chemotherapy, stereotactic body radiation therapy (SBRT) with MRgART, and PD with vascular reconstruction. Following PD, the incidence of iatrogenic PVS was 3.4% to 6.1%, which can be associated with significant morbidity as well as a 3% mortality rate secondary to gastric bleeding.[1-4] The risk factors for the development of PVS were tumor location in the pancreas,

Figure 2. Computed tomography contrast-enhanced axial (top row) and coronal (bottom row) images of the portal vein (red arrow) following simultaneous modulated accelerated radiation therapy preoperative (A), postoperative (B), and at the development of symptomatic ascites (C).



delivery of chemoradiation, and concomitant PV resection.[4] The patient, for example, developed both symptomatic ascites and bleeding varices as a result of PVS. Thus, it is important to continue to describe this phenomenon and offer potential etiologies and methods of mitigation.

Pancreatic surgery and porto-mesenteric reconstruction are known risk factors in the development of PVS due to inflammation, narrowing at the anastomotic site, and pancreatic leak.[4-6] Ten days after PD with vascular reconstruction, 84% of patients have some degree of concentric or eccentric vascular stenosis.[6] In patients with pancreatic cancer assessed 5 years after PD, it was found that vascular resection confers 3.28 times the risk of developing PVS—increasing it from 17% to 51%.[4]

Neoadjuvant chemotherapy may separately partially contribute to PVS. Two common chemotherapy regimens include gemcitabine and oxaliplatin. Gemcitabine monotherapy has been associated with coagulation cascade activation and endothelial damage and has been linked to increased thrombotic events, as well as increased risk when used in multiagent regimens.[7,8] Oxaliplatin has been linked to hepatic sinusoidal obstructive syndrome (SOS) in colorectal cancer due to chronic injury to endothelial cells; however, there is limited literature documenting oxaliplatin-induced hepatic SOS with respect to pancreatic cancer.[9] Discussion of this phenomenon may be limited in patients with pancreatic cancer due to more limited survival and, thus, follow-up.

Regarding radiation therapy (RT), radiation-induced vascular inflammation, thrombus, and stenosis are well-described phenomena, and the pathology is generally thought to be limited to small caliber vessels in the myocardium or mandible.[10-13] Reports on PVS after neoadjuvant chemoradiation are limited[7]; however, a recent prospective study reported the safety of MRgART for patients with locally advanced or borderline resectable pancreatic cancer.[14] After neoadjuvant chemotherapy, patients were treated to 50 Gy in 5 fractions and a total of 44 patients (32%) proceeded to surgical resection, with more than half of the patients requiring vascular reconstruction (n = 23). Two patients experienced grade 5 toxicities of fatal gastrointestinal bleeding that were deemed possibly related to MRgART. Additionally, the 3 postoperative deaths in the study occurred in patients who had vascular reconstruction more than 5 weeks from the completion of radiation. In the study, there were no published PV dose constraints; as a result, we adopted a D0.03 cm^3 (maximum dose

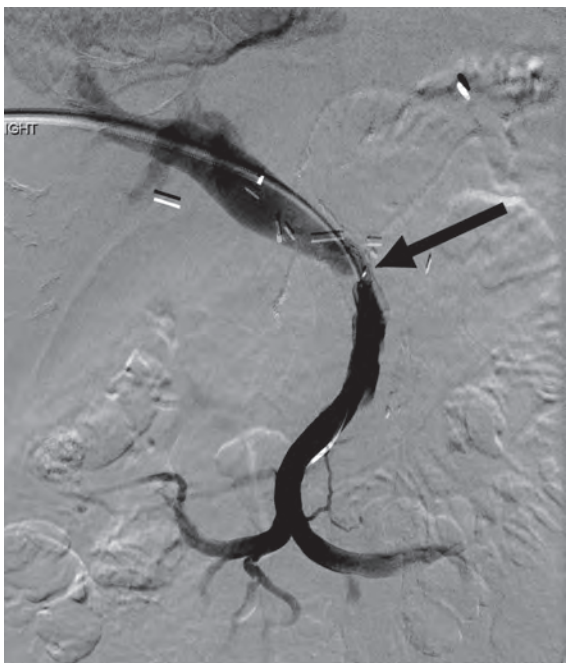


Figure 3. Transhepatic portal venography demonstrated stenosis of the main portal vein (PV) at the superior mesenteric vein orifice (arrow) and chronic occlusion of the splenic vein at the confluence with the main PV.

to 0.03 cm^3) of 50 Gy for the PV for all patients being treated with 5-fraction RT. We also included vascular injury in the informed consent form when planning RT to an upper abdominal disease site.

Nonetheless, acute-onset PVS may present with rapidly progressive abdominal ascites and endovascular therapies such as angioplasty and stenting can be performed in the setting of iatrogenic or tumor-related PVS. The success rate of stent deployment is approximately 93%, with median patency rates of at least 14 months.[3,15] The primary stent patency in stenting performed for tumor-related PVS was found to be shorter than that for iatrogenic

Table 1. Imaging Timeline

DATE	EVENT/IMAGING TYPE	FINDINGS
September 2022	Initial presentation	-
October 2022	MRI	3.8 × 3.2 × 4.0-cm mass in pancreatic head, along with a 1.3-cm left periaortic node. The mass included vascular encasement of the portosplenic confluence with associated narrowing. The mass also abutted both the PV and SMV, with > 180° of contact and contour irregularities associated with both vessels.
October 2022	PET	Negative for regional lymphadenopathy or distant uptake.
October 2022 to March 2023	Chemoradiation	-
March 2023	CT	Pancreatic mass had decreased from 3.8 cm prior to chemotherapy to 2.6 cm. There was a decrease in vascular involvement with respect to the PV and SMV, now with less than 180° of contact in both, although contour distortion was still present with respect to the SMV.
April 2023	Surgery	-
April 2023	CT	Small volume ascites, along with mild narrowing of the PV, moderate narrowing of proximal SMV, and occlusion or near occlusion of splenic vein adjacent to portal vein confluence without evidence of thrombus.
April 2023	US	Patent PV, but the SMV could not be visualized.
May 2023	US	Elevated velocity of the extrahepatic main portal vein, likely due to the superior stenosis at the portal SMV confluence.
July 2023	Paracentesis	-
August 2023	Endoscopic variceal clip	-
September 2023	Transhepatic portal venography	Stenosis of the main portal vein at the SMV orifice. Chronic occlusion of the splenic vein at the confluence with the main portal vein.
October 2023	CT	Significant narrowing of the portal venous confluence.

Abbreviations: PV, portal vein; SMV, superior mesenteric vein; PET, positron emission tomography; CT, computed tomography; US, ultrasound

PVS, at 6.5 months compared with 16 months, respectively.[15] After stenting, 71% to 93% of patients reported clinical improvements in symptoms, with major complication rates of 0% to 7%.[16–18] However, rapid symptom recurrence after stent deployment for radiation-induced venous disease within the lower extremities has been described, which suggests radiation changes may make intraluminal stenting less successful compared with stenting of non-irradiated veins.[19]

We acknowledge several limitations in reviewing and reporting this rare toxicity. The patient had heterogeneous treatments, which make identification of a single inciting factor difficult, and we suspect that the development of PVS is multifactorial. Importantly, the patient's variceal bleeding occurred prior to ascites, which we suspect was predominantly driven by splenic vein occlusion at the PVS rather than the PVS alone. We also acknowledge that there is likely a much larger group of patients with subclinical PVS without the need for therapeutic paracentesis or endovascular intervention if there is no significant pressure gradient across the vessel. Therefore, the incidence of PVS is likely under-reported in the literature.

Conclusion

Although rarely reported in the literature, PVS is a clinically significant side effect in patients with pancreatic cancer, which may be compounded by multimodality therapy. Although the cause of PVS in this population is not clearly identified and likely multifactorial (eg, extrinsic tumor compression, thrombus, narrowing at the venous anastomotic site, radiation-related vascular changes, and possibly underappreciated vascular and hepatic sinusoidal toxicity from FOLFIRINOX), its incidence and the potential influence of preoperative radiation should not be trivialized. Until clear dosimetric factors mitigating the risk of this phenomenon are more clearly defined, we caution against excessive radiation dose near the PV in operable patients and strongly recommend the adoption of PV dose constraints for patients planned for 5-fraction SBRT.

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A Rare Case of Sweat Gland Carcinoma of the Breast

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Abstract

Sweat gland carcinoma of the skin is a rare malignancy. Malignant sweat gland carcinoma of the breast is among one of the rarer sites of sweat gland malignancies, making it a very rare entity. with few cases reported in the literature. Sweat gland malignant lesions can arise in eccrine or apocrine sweat glands present in the skin. Here we report a case of malignant sweat gland carcinoma of the breast with axillary nodal metastasis treated with surgery (modified radical mastectomy) followed by adjuvant radiation therapy in view of lymph node metastasis.

Keywords: sweat gland carcinoma, breast, case report

Case Summary

The patient is a 68-year-old woman with no associated medical comorbidities and no family history of malignancy. She had presented with an ulcerated fungating right breast mass lesion in July 2021. She had noticed this lesion first in 2014. Over 7 years, the lesion had gradually progressed to the present size. She was initially evaluated by a surgical oncologist in July 2021. Clinical examination revealed an ulcerated right breast mass lesion measuring 10 × 10 cm involving the central part of the breast. It also showed that the nipple-areola complex appeared involved, the lesion was mobile and not fixed to the chest wall, palpable right axillary lymph nodes, and no clinical evidence of palpable supraclavicular nodes. Clinical examination of the opposite breast was normal. Breast lesion tissue biopsy showed features of malignant sweat gland carcinoma. A staging workup with ultrasound of the abdomen and pelvis and a CT scan of the chest showed no evidence of distant metastasis. The patient underwent modified radical mastectomy with axillary lymph node dissection in August 2021. Histopathology showed (**Figure 1**) features suggestive of high-grade malignant sweat gland carcinoma (skin adnexal tumor), a 10 × 7-cm tumor, no ductal carcinoma in situ, lymphovascular invasion (LVSI), nipple and areola involvement, skin involvement, tumor-free resected margins, and axillary lymph nodes that were 3/18 positive for metastasis with the pathological stage pT3 N2 as per the TNM (tumor, node, mestastasis) 8th edition for cutaneous adnexal tumors.

In view of the locally advanced nature of the primary tumor and presence of high-risk pathological features (large tumor size, LVSI, and nodal involvement), the patient received adjuvant locoregional radiation therapy (**Figure 2**). The internal mammary node region was not included in the field of radiation as there was no radiological evidence of disease or data showing any significant benefit to using this treatment for sweat gland carcinoma of the breast.

Radiation therapy dose prescription:

Phase 1: Planning treatment volume (PTV), which includes the chest wall, axilla, and

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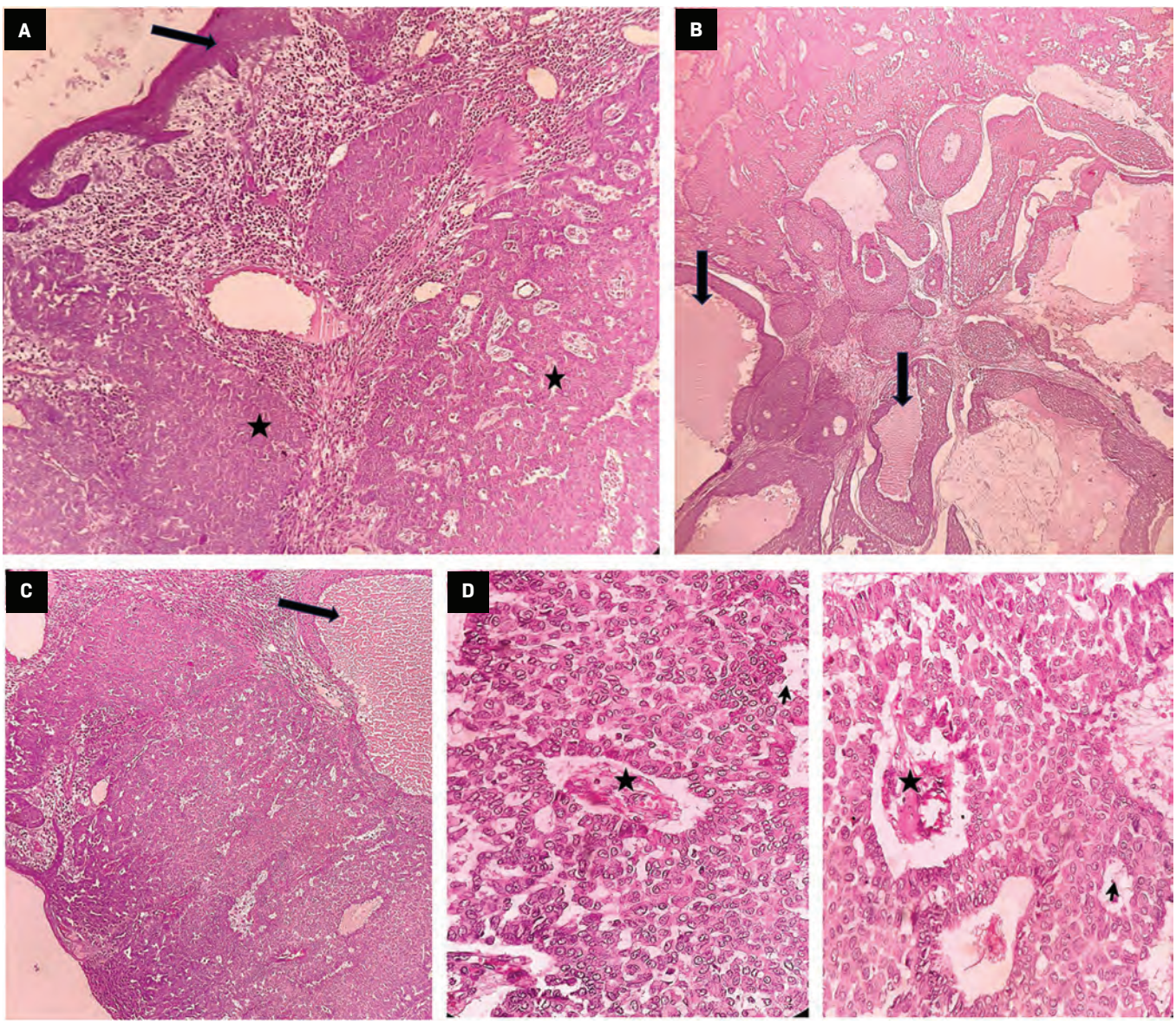
Figure 1. Section shows tumor-infiltrating dermis (star) arranged in nests and a glandular pattern with overlying intact epidermis (arrow) (hematoxylin and eosin [H&E] × 40) (A). Tumor shows the formation of duct-like structures (arrows) filled with secretions suggestive of sweat gland differentiation (H&E × 40, H&E × 100) (B). Tumor shows the formation of duct-like structures (arrows) filled with secretions suggestive of sweat gland differentiation (H&E × 100) (C). Both figures: tumor is composed of round to oval cells arranged in solid, papillary (star) and tubular (arrow) patterns (H&E × 400) (D).



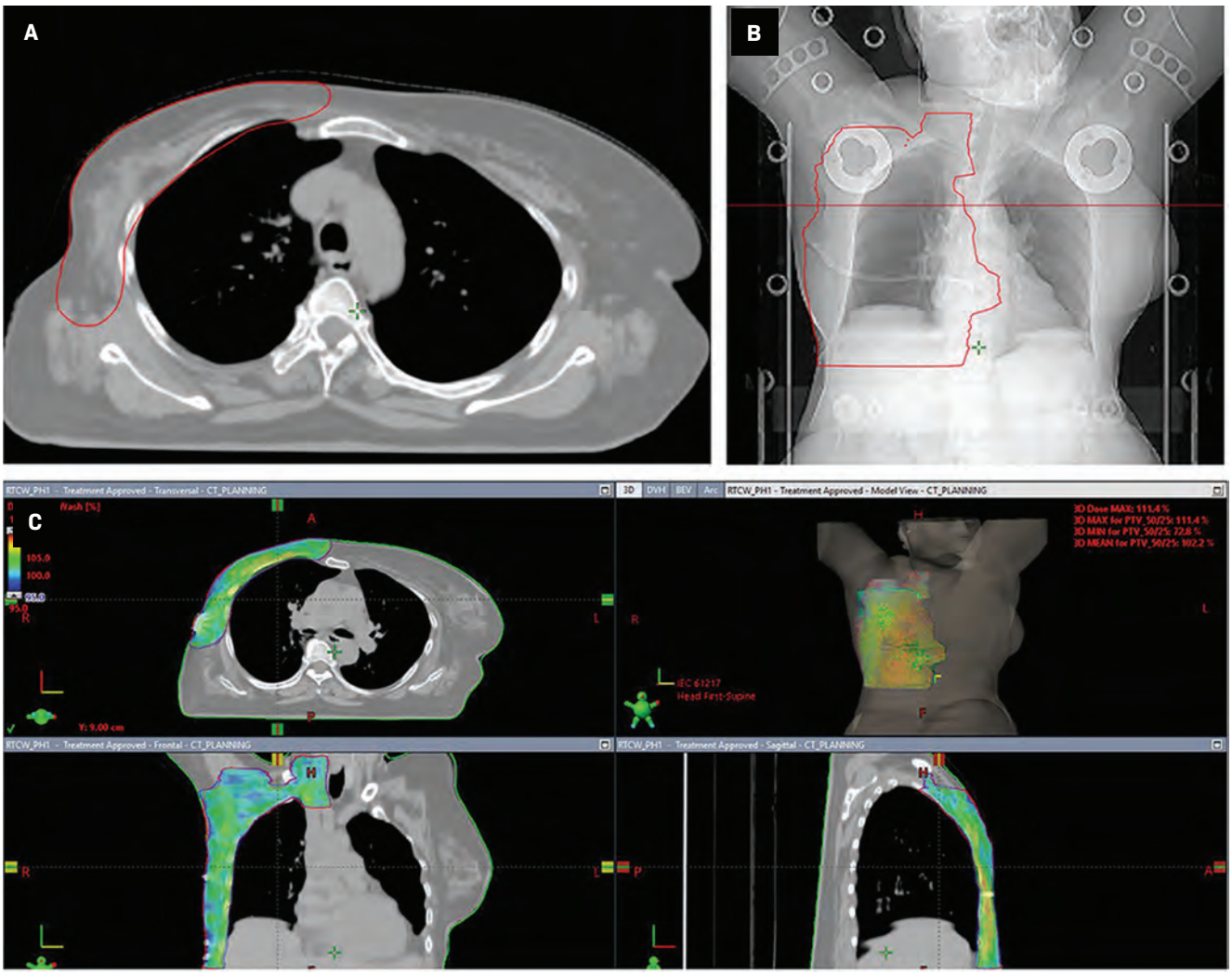
supraclavicular nodal region, 50 Gy in 25 fractions, 2 Gy per fraction, with the TrueBeam (Varian) linear accelerator using 6 MV photons with the RapidArc technique. A 5-mm gel bolus material was used to cover the chest wall target region (including the surgical scar and drain site) to have adequate radiation dose buildup over the skin of the chest wall.

Phase 2: PTV boost, which includes the chest wall surgical scar and drain site, of 10 Gy in 5 fractions, 2 Gy per fraction with 6 MeV electrons.

The patient tolerated the treatment well with grade 3 skin reactions, which recovered well by her first follow-up at 1 month. The patient was disease free as per the clinical examination and imaging (PET/CT) at the 1-year follow-up.

Diagnosis

Sweat gland carcinoma of the breast. The differential diagnosis includes other common cutaneous cancers such as basal cell carcinoma, squamous cell carcinoma, or



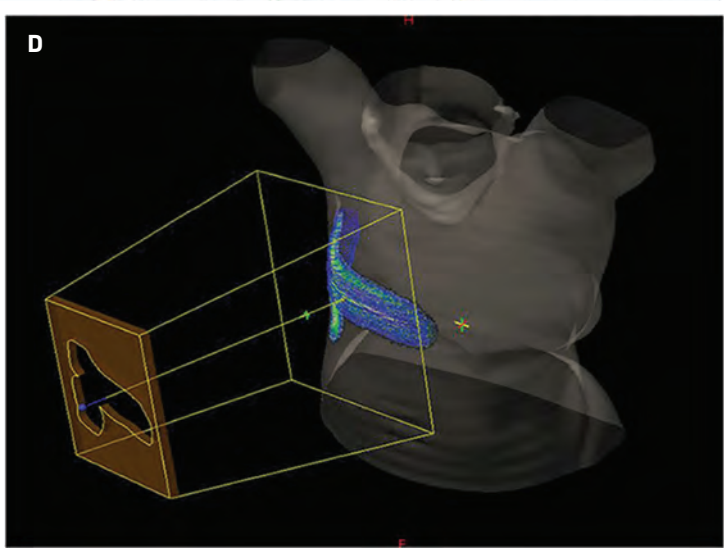


Figure 2. Radiation therapy treatment planning simulation CT image and primary treatment volume contour as visible ondigitally reconstructed radiographs (A, B). Radiation therapy dose distribution in color wash covering the chest wall, axilla, and supraclavicular nodal region (C). Electron-beam radiation therapy plan showing dose distribution covering the chest wall scar and drain sites (D).

metastatic carcinoma of the skin. Other possible differentials include hidradenoma and primary ductal breast malignancy.

Discussion

Sweat gland malignant lesions are a rare entity in clinical practice. The reported incidence in the literature is around 0.005% of all tumor specimens resected surgically.[1] These malignant lesions can arise from 2 anatomically different types of sweat glands in the skin: apocrine or eccrine. The main difference between apocrine and eccrine sweat glands is that the secretions of the apocrine sweat glands are viscid, whereas the secretions of eccrine sweat glands are watery. Furthermore, apocrine sweat glands are always connected to hair follicles while eccrine sweat glands are not. Apocrine sweat glands are predominantly present in the axillary and perianal region, whereas eccrine sweat glands are present all over the skin. The breast (mammary gland) is also considered a modified apocrine sweat gland. Sweat gland carcinoma arises from skin appendages in the dermis.[2] Exposure to ultraviolet rays has been suggested as an etiological factor.[3] Immune suppression has also been considered an etiological factor for development of eccrine carcinoma.[4]

Sweat gland carcinomas occur primarily in adults, with peak incidence in the fifth and sixth decades of life.[5-7] The majority occur in the genital skin and perineum (34.5%), followed by the trunk (26.4%), head and neck (18.3%), and lower extremities (13.9%).[5,6,8,9] The reported incidence is the same in men and women.[10] Tumors usually present as a solitary nodule or a plaque on the skin, and a history of rapid growth of the lesion suggests malignancy. These lesions have the tendency to infiltrate locally and also have regional nodal or sometimes distant metastasis.[11] Malignant sweat gland carcinoma of the breast is a rare site for a sweat gland malignancy, making it a very rare entity with few cases reported in the literature.

Histological evaluation, along with immunohistochemistry, is important in distinguishing these lesions from breast parenchymal malignant lesions. Microscopically they have the appearance of an adenocarcinoma with well-developed glandular lumina, showing characteristic evidence of "decapitation secretion."[12] Tumor cells are PAS (periodic acid-Schiff)-positive due to glycogen granules; they are also diastase resistant.[5] Other features include a glandular lumen, which may be narrow or slightly dilated with the cells of glandular and papillary structures being large, with a strongly eosinophilic cytoplasm containing hemosiderin.[12] Sudan stain for lipids may be either negative or positive with mucin often present in and around the lumen of the glandular structures.[12]

Because malignant sweat gland carcinoma of the breast is rare, no standard management guidelines exist. Surgery is the preferred upfront treatment for nonmetastatic operable lesions. For primary apocrine sweat gland carcinoma, wide local excision with regional lymph node dissection is considered for clinically node-positive disease.[3] For clinically node-negative disease, prophylactic lymph node dissection remains controversial.[3] Some studies have shown that prophylactic lymph node dissection has no influence on survival in these patients.[12,13] However, several case reports have found that sentinel lymph node biopsy is useful in these patients.[14,15] The local recurrence rate is high after surgery,[16] and the role of postoperative adjuvant treatment remains unclear.[3] Because weat gland carcinoma is generally considered resistant to chemotherapy, adjuvant chemotherapy is not routinely recommended.[17,18] However, in metastatic setting, chemotherapy has shown favorable responses.[19,20] Radiation therapy has a role in adjuvant setting as it reduces the risk of relapse.[18] It has been suggested that adjuvant radiation therapy should be considered if the disease has 1 or more risk factors such as T size of 5 cm or more, positive margins, a moderate to poorly differentiated tumor, or LVSI.[18] Prognostic factors for sweat gland carcinoma are difficult to identify owing to the small number of reported cases. The likely prognostic factors include tumor size, histological type, lymph node involvement, and distant metastasis.[11] A 10-year disease-free survival rate of 56% in the absence of lymph node metastasis is observed, which falls to 9% if nodes are involved.[5] In the largest retrospective cohort study, the median overall survival and 5-year disease-specific survival rates were 51.5 months and 88%, respectively.[21]

Conclusion

Malignant sweat gland carcinoma of the breast is a rare entity in clinical practice. These tumors are locally invasive and have a predilection for early nodal metastasis and, rarely, distant metastasis. Curative therapy involves upfront surgery for operable cases. Currently, there is a lack of specific management guidelines for adjuvant therapy. Adjuvant radiation therapy should

be considered in locoregionally advanced cases with high-risk pathological features for better local control. Currently, there is no significant role of adjuvant chemotherapy for malignant sweat gland carcinoma of the breast.

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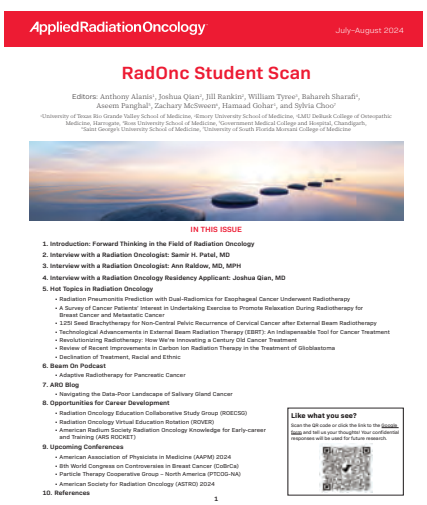
AppliedRadiationOncology July–August 2024

RadOnc Student Scan

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1

The Student Scan enewsletter is a wonderful quarterly resource written for students by students and presents interviews with radiation oncologists, synthesized hot topics, field opportunities, and more. *ARO* also features a biweekly enewsletter for subscribers, which highlights industry news and updates regarding journal activities.

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Advancing Resident Education: A Spotlight on ARRO's Education Initiatives

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Dr. Corrigan is a PGY5 resident physician, The University of Texas MD Anderson Cancer Center.

Dr. Ogunmuyiwa is a PGY3 resident physician, NewYork-Presbyterian Brooklyn Methodist Hospital.

As members of the Association of Residents in Radiation Oncology (ARRO) Executive Committee, the education subcommittee is dedicated to enhancing the educational experience of radiation oncology (RO) residents nationwide. Through a myriad of projects and collaborations championed by active membership and other ARRO subcommittees, we not only create and collate resources, but also leverage existing ones. Our primary goal is to support residents across the continuum of medical training and transition into practice. Here, we highlight ongoing and new initiatives for residents, in addition to ARRO's Favorite Resources.

Ongoing Projects and Collaborations

Webinars. We have worked alongside communications and advocacy subcommittees to provide a wide range of webinar topics and guest speakers. We have hosted a Visiting Professors series to highlight aspects of professional development less commonly discussed in residency, provided resources for radiology and treatment planning review, and reviewed clinical paradigms. We continue to keep trainees up to date on health policy and advocacy, most recently through a discussion of the Radiation Oncology Case Rate program. Collaborations with organizations such as Children's Oncology Group, Mednet, and ASTRO's Code Utilization and Application Subcommittee have enriched our webinar series, ensuring residents (and medical students) have access to a wealth of information.

At The Beam (ATB) Podcast. Our committee has successfully explored podcasts as another medium for the dissemination of educational material. We have partnered with ATB to bring ARROCases to the podcast in an oral boards format. Through short 15-to-20-minute episodes, ATB goes through RO cases, highlighting the relevant pearls in pathophysiology and management that are directly translatable to the clinic.

ARROCase and eContour. Monthly ARROCases created by subcommittee members review a case from diagnosis to follow up and serve as invaluable tools for residents, aiding in the preparation for clinics and exams. Additionally, our partnership with the eContour team allows us to seamlessly integrate ARROCases with eContour, creating a comprehensive resource for residents to refine their contouring skills.

High-Yield Radiation Biology and Physics Lectures. Our commitment to board preparation is evident in the release of high-yield physics and radiation biology lectures every 1 to 3 years, providing residents with essential knowledge to excel in their certifying exams.

Disclosures: All authors are members of ARRO's Executive Committee, and Dr. Basree is the ARRO representative to *Applied Radiation Oncology*; the authors have no other conflicts of interest to disclose. None of the authors received outside funding for the production of this original manuscript and no part of this article has been previously published elsewhere. ChatGPT version 3.5 was used for grammatical and stylistic edits after the manuscript was written.
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Shared Study Decks (ARROAnki). There is great heterogeneity in how residents learn and consolidate information needed to succeed in RO. Dedicated committee members have created and vetted shared study decks for several disease sites. This spaced-repetition, electronic flash card tool offers residents an efficient study resource tailored to their needs.

Varian Physics Study Guide. Varian has developed a physics study guide, which is a mix of videos and quizzes. This resource provides residents with a comprehensive resource for board exam preparation. Residents could register at this link: https://bit.ly/3wkV562.

Oral Boards Study Groups. Understanding the importance of oral boards and study groups, and through collaboration with the ASTRO Early Career Committee (ECC), our group was able to connect graduating residents across the country in small study groups. Make sure you check out the Tips & Tricks for success on ABR certifying Oral Examination co-hosted by ARRO and ASTRO ECC.

New Initiatives in Development

Entrustable Professional Activities (EPAs). In 2023, a study by Jeans et al[1] defined EPAs and curricular content domains in RO. Our team is closely working with the Radiation Oncology Education Collaborative Study Group to delve deeper into those critical competencies and develop a workbook to serve as an educational blueprint for stakeholders in residency programs and licensing bodies, ensuring consistency and excellence in resident training.

On-Call Initiative and Handbook. Led by residents within our committee, this collaborative effort aims to create a guide addressing common on-call/triage issues, enhancing preparedness and confidence among early RO residents.

RadOnc Questions (ROQ) Collaboration. Partnering with RadOnc Questions, we hope to incorporate ROQ quizzes to be released along with ARROCases, further cementing knowledge from the case in a set of high-quality board exam questions.

QuadShot Collaboration. Our collaboration with QuadShot aims to highlight resident-specific research, promoting original, high-quality work and engaging residents in the latest RO literature.

Awards

ARRO Resident Educator of the Year Award. We are proud to introduce this inaugural award recognizing outstanding dedication and innovation in resident education. This award celebrates the vital role of resident educators in shaping the future of health care and promotes excellence in teaching within our community.

ARRO Educator of the Year. We continue to award this honor to faculty members from each institution, recognizing their excellence and dedication to resident training and education.

In conclusion, we remain committed to advancing resident education through innovation, valuable resources, and collaborative partnerships. Our committee is comprised of a phenomenal group of dedicated individuals who have collectively made possible the above projects. We always welcome feedback, new ideas, and ways to improve and contribute meaningfully to resident education.

Reference

1) Jeans EB, Brower JV, Burmeister JW, et al. Development of a United States radiation oncology curricular framework: a stakeholder Delphi consensus. *Int J Radiat Oncol Biol Phys*. 2023;115(5):1030-1040. doi:10.1016/j.ijrobp.2022.12.009

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Dr. LeCompte is a PGY4 resident physician, Johns Hopkins University School of Medicine.

Erratum to: Ponce SB, LoTemplio A, Kaya E, et al. Adapting to the virtual world: an analysis of remote work policies in academic radiation oncology. *Appl Radiat Oncol.* 2024;13(1):6-14.

The authors of "Adapting to the Virtual World: An Analysis of Remote Work Policies in Academic Radiation Oncology" realized an error regarding the article's references. On p. 12, the following text had an incorrect citation and reference, which should have read as follows:

> While telemedicine has drawbacks, it allows for increased access to health care, as patients do not need to travel to their appointments and can decrease lost wages or other financial burdens of attending physician appointments. Additionally, patients who are immunocompromised, such as cancer patients, can have their appointments without being exposed to other patients who may spread infectious diseases in an office setting.[9]

9) Shih KK, Anderson AE, Brown J, et al. Stay home, work safe: attitudes and beliefs of members of a department of palliative care, rehabilitation, and integrative medicine regarding remote work during the COVID-19 pandemic. *J Palliat Med.* 2022;25(5):757-767. doi:10.1089/jpm.2021.0343

The addition of the new reference 9 prompted the subsequent citation and reference to change from 9 to 10.

Additionally, the first name of one of the authors was misspelled. The correct spelling is Shraddha M. Dalwadi, MD. The article has been corrected online and can be accessed at doi:10.37549/ARO-D-24-00003.

Erratum to: Silverwood SM, Lichter KE, Stavropoulos K, et al. Assessing the readiness for climate change education in radiation oncology in the US and Canada. *Appl Radiat Oncol.* 2024;13(1):15-22.

The authors of "Assessing the Readiness for Climate Change Education in Radiation Oncology in the US and Canada" indicated that the initial publication contained errors in the reported sample size in Table 1, which resulted in incorrect percentage calculations. The corrected sample size and corresponding percentages are now provided. The authors apologize for any confusion this may have caused.

The article has been corrected online and can be accessed at doi:10.37549/ARO-D-24-00007.

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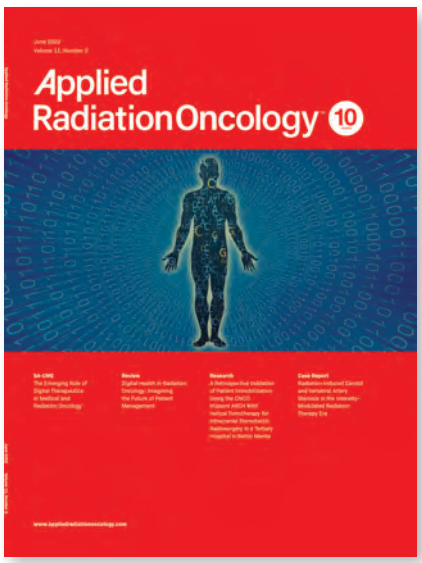

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