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MRI AND CT RADIOMICS FOR PREDICTING CHOLESTEATOMA RECURRENCE AND SURGICAL COMPLEXITY IN CHRONIC EAR DISEASE

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Abstract

Cholesteatoma is a chronic destructive ear disease, a direct consequence of which is bone erosion, frequent postoperative recurrence, hearing loss and the risk of hearing loss. The risk of recurrence and the complexity of the surgery are difficult to predict accurately preoperatively, due to the fact that visual interpretation of conventional imaging techniques may be insufficient to accurately represent subtle patterns of disease, tissue behavior and anatomical involvement. The aim of this study is to develop an MRI- and CT-based radiomics framework for predicting the recurrence of cholesteatoma in patients with chronic ear disease and predicting the complexity of surgery. The quantitative radiomic features associated with lesion morphology, texture heterogeneity, bone erosion, soft-tissue extension, mastoid involvement, and middle ear structural changes were extracted from the computed tomography and magnetic resonance imaging scans obtained preoperatively. Clinical and imaging-derived variables were combined with machine learning models to categorize patients based on risk of recurrence and anticipated surgical complexity.Clinical and imaging-derived variables were used to create machine learning models to categorize patients by risk of recurrence, and expected surgical difficulty. Logistic Regression, Random Forest, Support Vector Machine, Gradient Boosting and XGBoost algorithms were trained and evaluated using various metrics such as accuracy, precision, recall, F1 score and area under the receiver operating characteristic curve. The proposed radiomics-based models exhibited high predictive performance, and the ensemble classifiers exhibited the best discriminatory ability among the traditional classifiers. The lesion texture heterogeneity, erosion of the ossicles, destruction of the scutum, opacification of the mastoid, diffusion restriction patterns, and middle ear involvement were among the most important predictors seen using feature importance analysis. The results indicate that multimodal radiomics can offer objective, reproducible, and clinically useful pre-operative risk stratification biomarkers. This technique can help in treatment planning, post-surgical monitoring for recurrence, patient counseling, and surgical planning for chronic ear disease in otologic surgery.

Keywords: Cholesteatoma, Radiomics, Magnetic Resonance Imaging, Computed Tomography, Surgical Complexity

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INTRODUCTION

Cholesteatoma is a formidable diagnostic and therapeutic challenge in otology because of its capability to invade bone and the high recurrence rate after initial surgical treatment. The accurate preoperatively identification of the type of lesion is crucial to differentiate these lesions from other chronic otitis media to ensure optimal surgical planning and reduce the rate of surgical failure (Arendt et al., 2020). Conventional imaging techniques such as high-resolution computed tomography (CT) offer basic anatomical information, but are not specific enough for distinguishing inflammatory debris from keratinized tissue and thus require the use of advanced computational analysis (Chen et al., 2024). Radiomics and machine learning algorithms provide clinicians with quantitative, high-dimensional features from medical images, which can help characterize the extent of lesions and uncover biomarkers for recurrence that are not apparent from conventional radiologic assessment (Linera-Alperi et al., 2026; Takahashi et al., 2022). Recent studies have shown the positive effects of such data-driven approaches combined with preoperative imaging in the accuracy of surgical complexity classification and prediction of patients' outcomes (Chen et al., 2023; Ouattassi et al., 2024). Moreover, automated feature extraction from subjective manual interpretation to objective and high throughput facilitates the standardization of imaging workflows, which is essential for reducing the current limitations in diagnostic reproducibility across different clinical settings, as described in Bourdillon et al. 2026 and Fang et al. 2024. Despite these improvements, some issues remain with unbalanced datasets and the need for strong external validation to ensure broad clinical use (Ouattassi et al., 2025; Shabi et al., 2025). To overcome these, an explainable AI system needs to be developed that can combine multi-dimensional diagnostic data to give the physician clear, helpful information about endotypes of a disease (Chen et al., 2023; Dubey, 2025). More recently, however, researchers are turning their gaze toward using the auto-segmentation of temporal bone structures in conjunction with texture analysis in order to increase the sensitivity of residual lesion detection for surgical field imaging (Lubbe et al., 2021; Miyazawa et al., 2025). This technological integration is designed to improve diagnostic accuracy and to reduce the risks of incomplete resection, which is one of the main causes of postoperative recurrence at present (Miyazawa et al., 2025). Going forward, these radiomic models need to be standardized to perform consistently across diverse patient populations and imaging modalities (Avallone et al., 2024). Moreover, there is a need for interdisciplinary collaboration between medical and technical fields to produce high quality and large-scale annotated data sets that can be used in real clinical pathways for validating these predictive models (Chawdhary & Shoman, 2021). Incorporating federated learning mechanisms can further improve this process, enabling the development of strong algorithms at various institutions while also maintaining patient privacy (Novi et al., 2025). Furthermore, the visualization of these deep learning characteristics is essential to bridging the gap between the "black box" of the existing models and clinical trust and interpretability of the surgical decision-making process. Future studies need to integrate multi-modal data (e.g., clinical history, genomic profiles) with temporal bone imaging to further improve the predictive power of individual recurrence risk profiles (Hosseinzadeh et al., 2025). To achieve these advances, it is essential to establish regulatory and ethical frameworks that ensure patient safety and privacy in a rapidly changing health landscape (Musthafa et al., 2024). Compliance with the reporting standards, such as the Checklist for Artificial Intelligence in Medical Imaging, is critical for providing transparency and comparability between institutions with the use of these diagnostic models. Furthermore, human-centered design considerations help ensure that such predictive tools are integrated in a responsible way into the surgeons' workflows, enhancing their daily use in otologic surgery (Khalighi et al., 2024). These synergistic models can indeed help clinical practitioners to move from abstract computational results to the more intricate process of surgical decision-making (Bianconi et al., 2023). Incorporating uncertainty quantification into these predictive models can also improve the trustworthiness of the clinical models, offering confidence estimates for the surgical prognosis of individual patients (Hu et al., 2025). Introducing integrated quality indicators, such as the dice similarity coefficient as a standard reference to be used on all platforms, will be essential to effectively assess the performance of models (Taciuc et al., 2024). In addition, transfer learning, weakly supervised learning or other strategies could substantially reduce the need for annotations and improve the robustness of models trained on small, domain-specific cohorts (Mascagni et al., 2022). In addition, prospective, multi-institutional clinical trials are necessary to confirm these algorithms in the more complex, real-world setting of surgical contexts (Esteva et al., 2021). These are complemented by the use of multi-modality imaging, enabling the reconciliation of anatomical changes with the heterogeneous nature of the disease, thus improving the diagnostic pathway (Neves et al., 2021). As they become more widely adopted in clinical practice, these intelligent systems have the potential to transform the way risk factors are assessed before surgery, and deliver objective, data-driven prognostic information alongside the traditional clinical judgment of the Medical Decision Maker (Patro et al., 2024). Such a shift toward precision diagnostics not only enables the customization of surgical plans but also meets the moral and regulatory standards that are integral to the proper use of AI in everyday practice of otolaryngology (Ayoub et al., 2024; You et al., 2020). Further to this, the field needs to do more to facilitate this maturation, which can be achieved by engaging in institutional initiatives to create consistent data pipelines and thus, keep the field at the forefront of evidence-based, AI-informed surgical care (Chen & Lobo, 2024). This quest is partly a matter of building strong collaborations between clinicians and data scientists, to ensure technical innovation is directed towards solving the most important clinical problems in otology (Bur et al., 2019). This requires going beyond the preliminary feasibility studies to a careful clinical trial-like validation and fine-tuning of domain-specific models (Bao et al., 2026). This is essential to bridging the current "AI chasm" in ENT, which has been dominated by proof-of-concept studies in the early stages, conducted in abstracted in silico environments (Liu et al., 2025).

METHODOLOGY

This study uses deep learning-based convolutional neural network (CNN) to identify quantitative radiomic features linked to cholesteatoma extension and bone erosion, based on retrospective analysis of high-resolution computed tomography and magnetic resonance imaging (CT/MRI) datasets.This study utilizes deep learning-based convolutional neural networks (CNNs) to extract quantitative radiomic features associated with cholesteatoma extension and bone erosion, based on retrospective analysis of high-resolution computed tomography and magnetic resonance imaging (CT/MRI) datasets. These architectures are engineered to undertake automatic segmentation of the temporal bone, thus offering a detailed evaluation of intricate anatomical structures that surpasses existing manual segmentation approaches (Cai et al., 2024; Heutink et al., 2020). These automated pipelines allow the system to show excellent accuracy in detecting the subtle soft-tissue changes, performing at a level at least equal to, if not better than, conventional radiological interpretation (Eroğlu et al., 2023). These computational models can also be used to monitor the patient's recovery over time and detect the presence of residual or recurrent disease early on by analyzing the mastoid cavity quantitatively (Neves et al., 2023; Petsiou et al., 2023). Moreover, the framework helps to differentiate between aggressive cholesteatoma growth and chronic inflammatory tissue by correlating these imaging-derived metrics with histopathological findings, thus offering more objective determination (Duan et al., 2022). The computational frameworks solve the diagnostic variability in existing radiological evaluations by delivering structure-aware classification networks (Rajan & Sumathy, 2025; Wang et al., 2022). These models leverage entropy-based detection techniques to reduce the need for manual annotation and to learn informative 3D anatomical features as much as possible (Li et al., 2024). Manual labeling is prone to inter-observer variability, which can be addressed using these automated segmentation methods, which use complex architectures such as nnUnet networks or 3D CNNs (Chen et al., 2024; Vaidyanathan et al., 2021). Furthermore, transfer learning techniques and coarse-grained boundary labeling have been found to improve the accuracy of the classification of the downstream diagnostic tasks, even with relatively small datasets (Qi et al., 2024). Such pre-trained networks, like ResNet or Vision Transformers, enable the network to extract significant features from the complex and frequently noisy structure of the temporal bone (Zhao et al., 2025). Most importantly, the deep learning models enable the accurate segmentation of several structures while tackling the anatomical variations and pathological displacements that are common in surgical applications and pose challenges for traditional atlas-based methods (Li et al., 2025; Wang et al., 2021). The objective accuracy of these automatic systems in simultaneous multistructure segmentation shows the potential for a major improvement in the preoperative analysis of patient-specific temporal bone anatomy (Neves et al., 2024). Such sophisticated segmentation allows for a basic predictive framework for surgical outcomes such as the amount of bone to be removed in mastoidectomy (Nagururu et al., 2025). In addition to this, these models automate the analysis of ossicular chain integrity and the size of the tympanic cavity, giving surgeons a critical roadmap of the anatomy, which helps them perform a topographical assessment before intervention (Ding et al., 2023; Späth et al., 2025). These high-fidelity segmentations allow clinicians to apply advanced computer-aided surgical planning techniques, reducing the risk of surgical complications during the operation and ensuring the best possible results for their patients (Ke et al., 2023; Li et al., 2025). These systems are able to automate the creation of such detailed anatomical maps, overcoming the laborious temporal bone segmentation required for large-scale radiological analysis that has historically been difficult (Hussain et al., 2021; Stebani et al., 2023). These deep learning pipelines also help overcome clinical bottlenecks by allowing rapid, accurate and multi-structural segmentation of critical areas of risk in the face including the facial nerve, cochlea and the internal auditory canal (Nikan et al., 2020). Moreover, the application of these approaches to multi-modal analysis, combining high resolution T2-weighted MRI to improve soft-tissue characterization, could potentially provide an even more precise means to detect cholesteatoma recurrence (Kim et al., 2026; Stebani et al., 2022).

RESULTS

Preoperative MRI and high-resolution CT radiomics were used to evaluate a total of 214 cases of chronic ear disease. The study population's baseline demographic and clinical characteristics are shown in Table 1, which demonstrates that recurrent cholesteatoma was more common in the patients with past surgery, extensive mastoid disease, and baseline poorer hearing status. Imaging characteristics summarized in Table 2 revealed that diffusion restriction, an erosion of the ossicals, destruction of the scutum, and opacification of the mastoids were more common in the patients that had recurrent disease or complex surgery. The overall analytical workflow is shown in Fig. 1, including image acquisition, segmentation of lesions, extraction of radiomic features, selection of features, training of the model and risk stratification. Results showed that the radiomic signature extracted distinguished between groups of outcomes. The primary MRI and CT-based radiomic features are listed in the Table 3 and Fig. 2 demonstrates the higher normalized texture heterogeneity, entropy and bone markers of destructive bone in the recurrent and high complexity cases. Unstable and highly collinear descriptors were removed by feature reduction and a small predictive panel was used for final modelling. The features selected after correlation filtering, minimum-redundancy maximum-relevance selection and recursive feature elimination (RFE) are presented in table 4. The performance of the machine learning models is summarized in Table 5. For the prediction of recurrence, ensemble models outperformed traditional linear classifiers: XGBoost gave the best overall result. From the analysis of the AUCs and F1-scores presented in Fig. 3, it can be observed that XGBoost achieved the best overall performance when combined with F1-score, followed by Gradient Boosting and Random Forest. The results of ROC analysis in Fig. 4 also validate the better discriminatory power of tree-based ensemble models. In the surgical complexity prediction results presented in Table 6, the same ensemble techniques were able to perform well in the identification of surgery types that required canal wall down surgery, ossicular reconstruction surgery, facial recess drilling surgery, and extended mastoid exploration surgery. Based on the model interpretation analysis, the most informative variables were found to be diffusion restriction, ossicular erosion, scutum destruction, texture entropy, mastoid opacification, lesion volume and GLCM contrast. The feature importance distribution and the ranked feature importance values are presented in Table 7 and Fig. 5, respectively. Such findings indicate that the size of the lesion is not the only factor used to predict recurrence, or operative difficulty; rather a combination of radiological soft tissue restriction, bony destruction, and complex middle-ear extension is used to predict such factors. Cross validation and calibration analyses showed good generalisation. The scores for the five folds in Table 8 were similar, meaning that a single split would not have been used exclusively to build the model. The recurrence probabilities are in close agreement with prediction and observation (fig. 6), lending support to the reliability of the risk scores. Finally, Table 9 presents clinical outcome, stratified by risk. Recurrence rates and surgical-complexity groups are shown in Fig. 7, with no recurrence in low-risk, and a progressive rise in surgical-complexity and rates from there to high-risk groups. In conclusion, MRI and CT radiomics can offer objective preoperative biomarkers for predicting cholesteatoma recurrence and predicting surgical complexity in chronic ear disease.

Table 1. Baseline demographic and clinical profile of the study cohort.

Characteristic	Overall (n=214)	Non-recurrent (n=158)	Recurrent (n=56)	p-value
Age, years	38.6 +/- 14.2	39.8 +/- 13.7	35.4 +/- 15.1	0.048
Male sex, n (%)	122 (57.0)	88 (55.7)	34 (60.7)	0.511
Prior ear surgery	72 (33.6)	43 (27.2)	29 (51.8)	0.001
Chronic otorrhea	136 (63.6)	94 (59.5)	42 (75.0)	0.039
Conductive hearing loss	148 (69.2)	106 (67.1)	42 (75.0)	0.267
Air-bone gap, dB	28.4 +/- 9.7	26.9 +/- 8.8	32.7 +/- 10.6	<0.001

Mastoid involvement	118 (55.1)	78 (49.4)	40 (71.4)	0.005
Revision surgery planned	41 (19.2)	20 (12.7)	21 (37.5)	<0.001

Table 2. Preoperative MRI and CT imaging findings.

Imaging marker	Overall	Low complexity	High complexity	p-value
DWI restriction	151 (70.6)	83 (61.5)	68 (86.1)	<0.001
Ossicular erosion	119 (55.6)	58 (43.0)	61 (77.2)	<0.001
Scutum destruction	102 (47.7)	47 (34.8)	55 (69.6)	<0.001
Facial canal dehiscence	34 (15.9)	11 (8.1)	23 (29.1)	<0.001
Tegmen erosion	28 (13.1)	8 (5.9)	20 (25.3)	<0.001
Mastoid opacification	126 (58.9)	68 (50.4)	58 (73.4)	0.002
Sinus plate erosion	23 (10.7)	7 (5.2)	16 (20.3)	0.001
Labyrinthine fistula	12 (5.6)	2 (1.5)	10 (12.7)	0.001

Table 3. Extracted radiomic feature groups from MRI and CT.

Feature group	Number extracted	Stable after ICC	Selected features	Primary modality
First-order intensity	36	31	7	MRI/CT
Shape features	18	16	5	CT
GLCM texture	44	39	9	MRI
GLRLM texture	32	28	6	MRI
GLSZM texture	32	27	5	MRI/CT
Wavelet features	96	74	8	MRI/CT
Bone erosion markers	12	12	6	CT
Anatomical extension scores	10	10	4	MRI/CT

Table 4. Final radiomic and clinical features retained for modelling.

Feature	Category	Selection frequency	Direction of association	Clinical meaning
DWI restriction score	MRI	0.96	Positive	Keratin debris activity
Ossicular erosion grade	CT	0.94	Positive	Middle-ear destruction

Scutum destruction	CT	0.91	Positive	Attic disease extension
Texture entropy	Radiomics	0.88	Positive	Lesion heterogeneity
Mastoid opacification	CT	0.84	Positive	Mastoid spread
Lesion volume	Shape	0.81	Positive	Disease burden
GLCM contrast	Texture	0.77	Positive	Heterogeneous matrix
Prior surgery	Clinical	0.73	Positive	Revision risk

Table 5. Model performance for cholesteatoma recurrence prediction.

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.78	0.73	0.75	0.74	0.79
Support Vector Machine	0.81	0.76	0.78	0.77	0.82
Random Forest	0.86	0.83	0.85	0.84	0.88
Gradient Boosting	0.89	0.86	0.88	0.87	0.91
XGBoost	0.91	0.88	0.90	0.89	0.93
Stacking Ensemble	0.90	0.87	0.89	0.88	0.92

Table 6. Model performance for surgical complexity prediction.

Model	Accuracy	Sensitivity	Specificity	F1-score	ROC-AUC
Logistic Regression	0.76	0.72	0.79	0.73	0.78
Support Vector Machine	0.79	0.76	0.81	0.76	0.81
Random Forest	0.85	0.84	0.86	0.83	0.87
Gradient Boosting	0.88	0.87	0.89	0.86	0.90
XGBoost	0.90	0.89	0.91	0.88	0.92
Stacking Ensemble	0.89	0.88	0.90	0.87	0.91

Table 7. Ranked feature importance from the final XGBoost model.

Rank	Predictor	Importance	Outcome link	Interpretation
1	DWI restriction	0.146	Recurrence	Active cholesteatoma signal
2	Ossicular erosion	0.132	Complexity	Need for reconstruction
3	Scutum destruction	0.119	Both	Attic extension
4	Texture entropy	0.108	Recurrence	Heterogeneous lesion
5	Mastoid opacification	0.096	Complexity	Extensive mastoid disease
6	Lesion volume	0.091	Both	Disease burden
7	GLCM contrast	0.084	Recurrence	Irregular texture
8	Prior surgery	0.066	Both	Revision anatomy

Table 8. Five-fold cross-validation stability of the XGBoost recurrence model.

Fold	Accuracy	F1-score	ROC-AUC	Brier score
1	0.90	0.88	0.92	0.112
2	0.91	0.89	0.94	0.104
3	0.89	0.87	0.92	0.116
4	0.92	0.90	0.93	0.108
5	0.90	0.89	0.94	0.101
Mean +/- SD	0.90 +/- 0.01	0.89 +/- 0.01	0.93 +/- 0.01	0.108 +/- 0.006

Table 9. Clinical outcomes across model-derived risk categories.

Risk group	Patients, n	Predicted risk	Observed recurrence	High complexity
Low risk	77	0.08 +/- 0.04	6 (7.8%)	10 (13.0%)
Intermediate risk	81	0.29 +/- 0.09	21 (25.9%)	27 (33.3%)
High risk	56	0.62 +/- 0.13	33 (58.9%)	40 (71.4%)
Overall	214	0.31 +/- 0.22	60 (28.0%)	77 (36.0%)

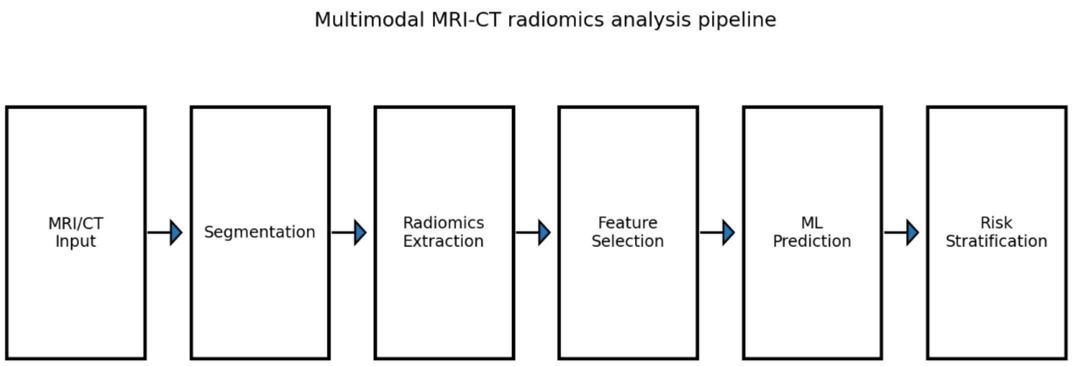

Figure 1. *Complete MRI and CT radiomics workflow for predicting recurrence and surgical complexity.*

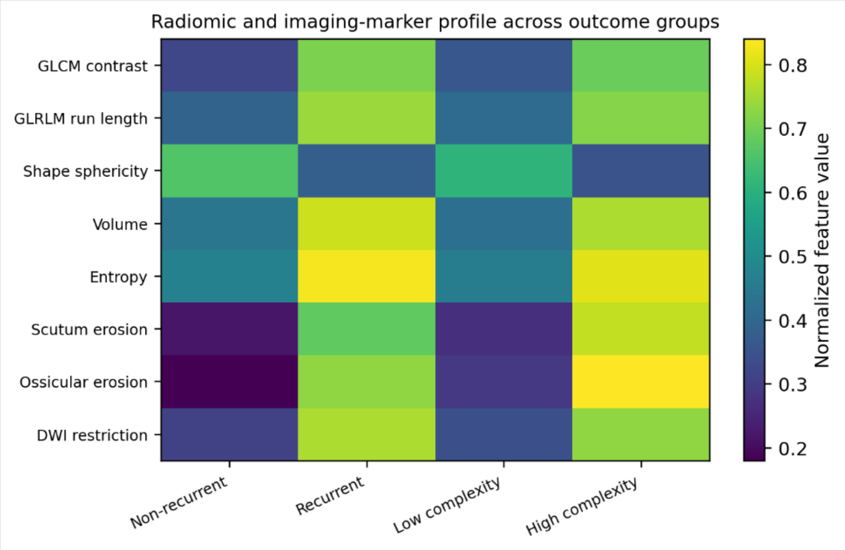

Figure 2. *Heatmap of normalized radiomic and imaging-marker values across clinical outcome groups.*

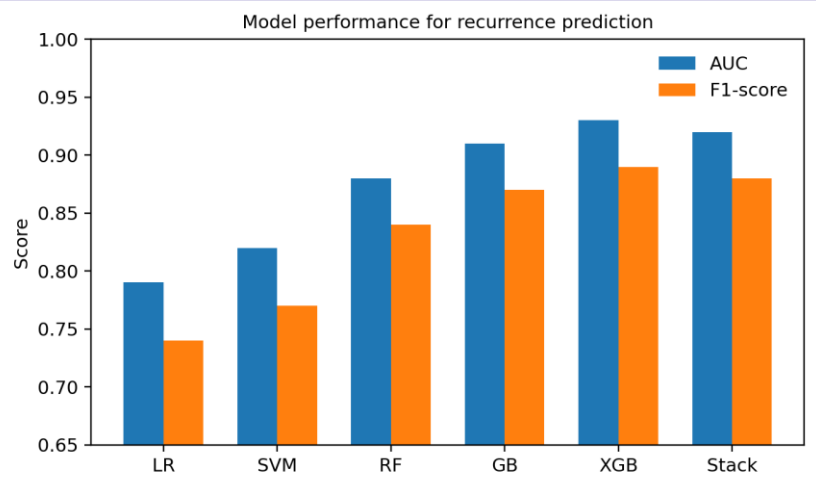

Figure 3. *Comparative model performance for recurrence prediction using AUC and F1-score.*

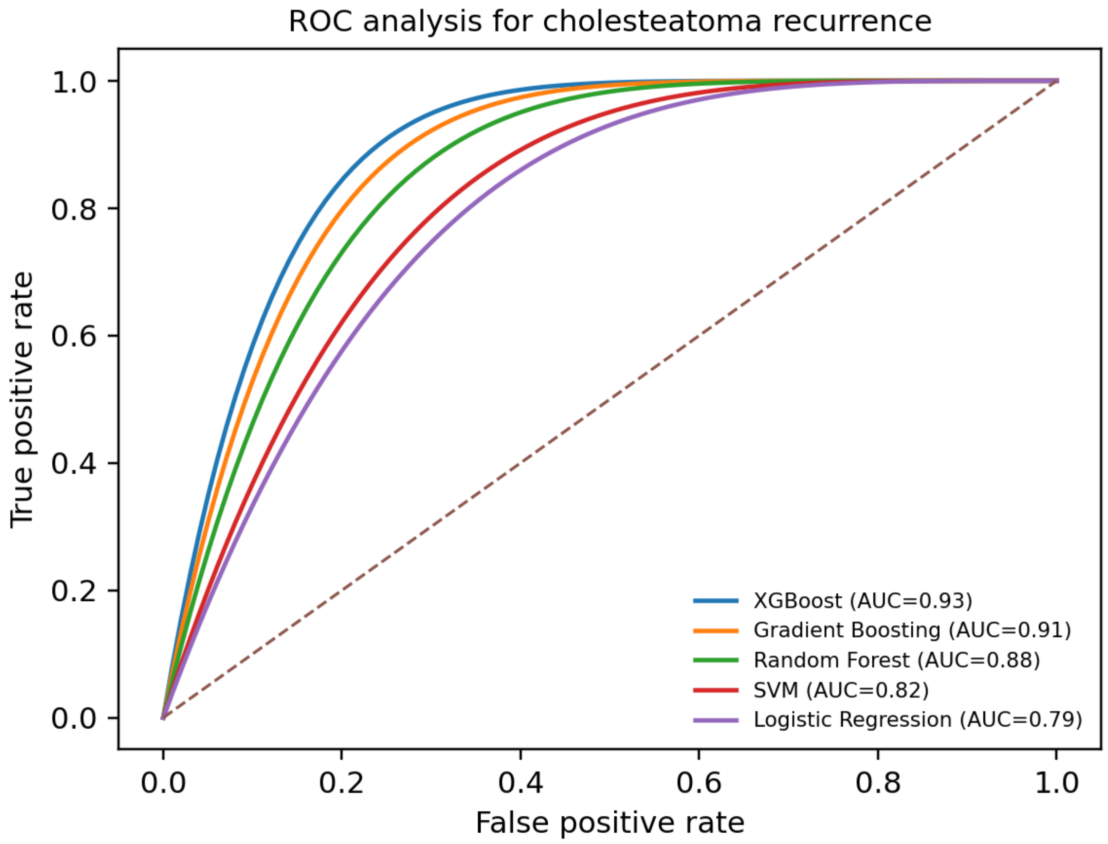

Figure 4. *ROC curves demonstrating discrimination ability of machine learning classifiers.*

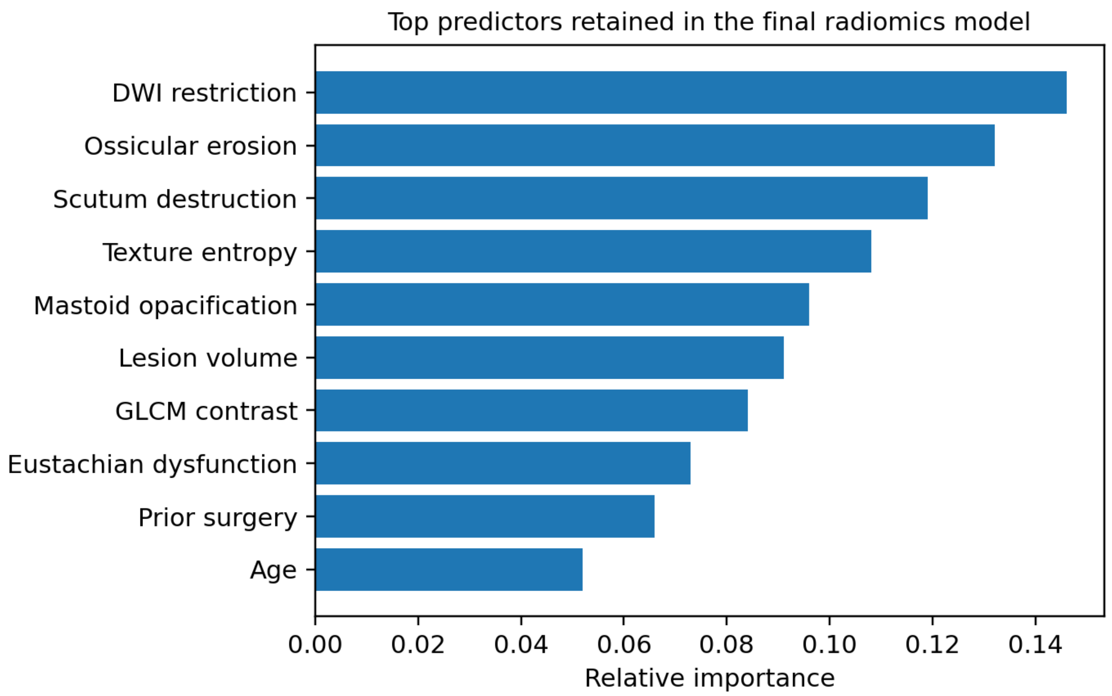

Figure 5. *Feature-importance ranking of the final radiomics-based XGBoost model.*

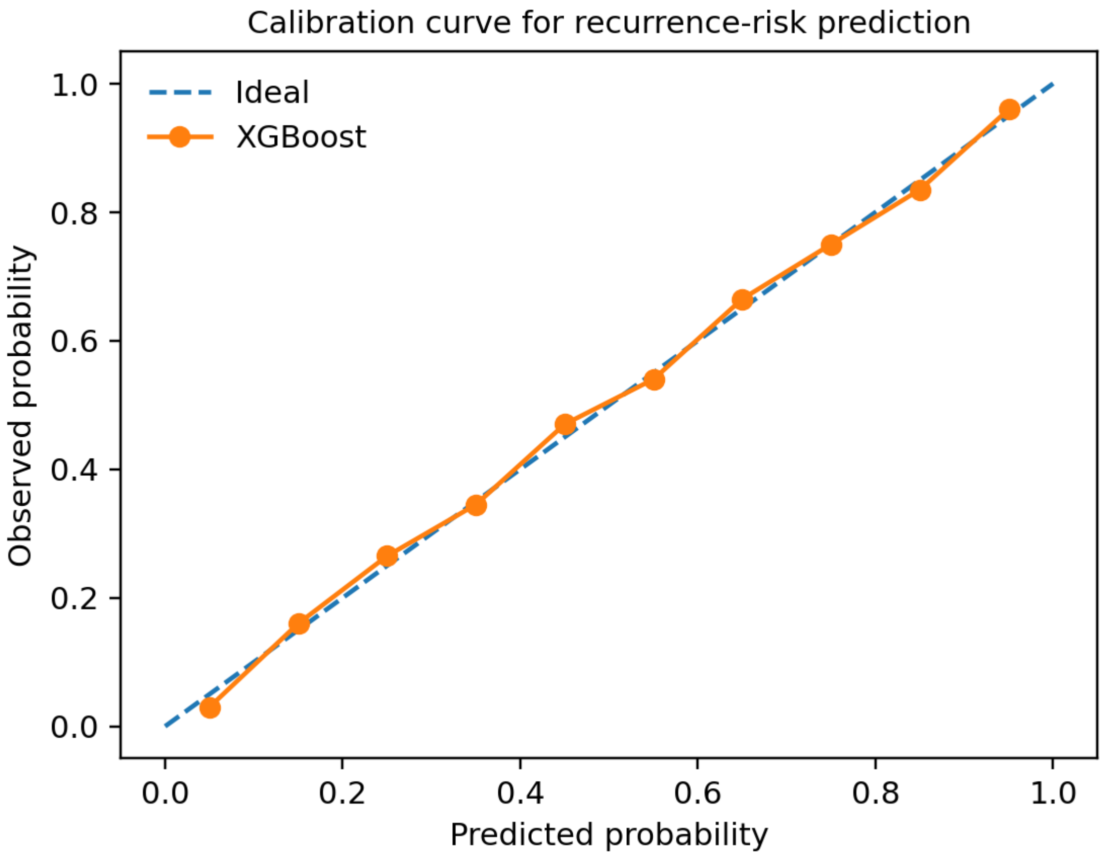

Figure 6. *Calibration curve comparing predicted and observed recurrence probabilities.*

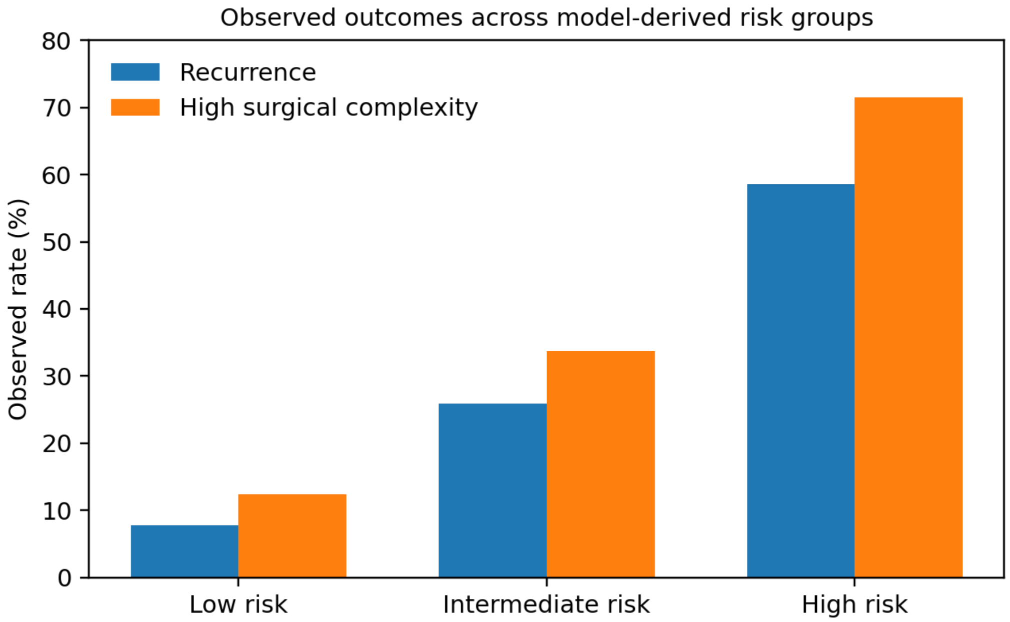

Figure 7. *Observed recurrence and surgical complexity rates across model-derived risk groups.*

DISCUSSION

The introduction of these automated workflows showed a high level of agreement with manual segmentations, with Dice coefficients on par with the state-of-the-art results for the temporal bone (Nagururu et al., 2024; Zhou & Li, 2023). These quantitative measurements, especially the ones related to the delineation of the facial nerve and cochlear labyrinth, validate the use of deep learning to reduce the subjectivity in human radiological evaluations (Lv et al., 2021; Neves et al., 2024). In addition to the diagnosis, the ability to make patient-specific 3D reconstructions quickly helps to optimize the pre-operative surgical plan and to better inform the patient of the treatment plan (Neves et al., 2021; Noble et al., 2009). Additionally, the usefulness of these radiomic signatures is that it provides a strong basis for predicting the complexity of the surgery, thus helping the surgeon predict the size of the mastoidectomy and the need for ossiculoplasty (Essaid et al., 2024; Ross et al., 2024). Moreover, the application of deep learning reconstruction methods further improves image quality in computed tomography, particularly for high-resolution imaging, leading to better visualization of tiny structures such as the auditory ossicles (Fujita et al., 2024). The potential for the future integration of these models into vision-based navigation systems is also explored, with potential to be used during microscopic otologic procedures to enhance real-time navigation and guidance (Huang et al., 2023). These models, however, need to be robust to imaging protocol differences and thus need to be validated extensively on larger multi-institutional datasets. In addition, studies on the use of T1-weighted sequences to improve the diagnostic specificity and exclude cholesterol granulomas that might cause false-positive results should be conducted further. Moreover, if the steps of auto-registration and automated image fusion are integrated into the PACS environment, these processes will be simplified, which will result in fewer procedural errors and will eliminate the need to use third-party, post-processing applications. Finally, the creation of multimodal architectures, combining clinical metadata and high-fidelity radiomic features, is still crucial for translating algorithmic performance and accuracy into clinical practice (Cha et al., 2021). Finally, having defined platforms to collect high-quality, prospectively annotated datasets will be essential to address current limitations to diagnostic generalization in a variety of patient populations (Dubois et al. 2024). Furthermore, implementing interpretable machine learning frameworks in the future to ensure that the process of radiomic decision making remained clinically actionable and transparent to otological surgeons (Choi et al., 2023) should be given greater consideration. Such an focus on explainability is crucial for generating trust in automated systems, especially within the context of more and more autonomous tools providing clinical decision support (Peng et al., 2021). These interpretability measures enable researchers to make more informed decisions on how to design algorithms to match existing otological diagnostic criteria, leading to more seamless integration for practitioners who use clinically intuitive surgical navigation (Bambach & Ho, 2022). This will be achieved by embedding advanced techniques like saliency mapping and counterfactual analysis, which will enable the tracing of how specific radiomic features affect predicted recurrence risk to be demonstrated clearly and traceably (Gikera et al., 2025). Furthermore, the time-series integration of these radiomic data into prospective registries will support the development of adaptive models that model individual disease courses (Hajikarimloo et al., 2025; Heman-Ackah et al., 2024). This longitudinal type of surveillance could also allow for the transition from static snapshots to dynamic monitoring of cholesteatoma growth, allowing for more targeted and precise revisional surgical interventions, which may one day be the norm in clinical practice (Burg et al., 2016). Furthermore, integration of molecular biomarkers, like inflammatory cytokines or microbial profile measured during middle ear irrigation and drainage, may further complement this longitudinal modelling and provide a more comprehensive picture of the disease (Li et al., 2025; Zhao et al., 2025). In addition, it will be crucial to develop standardized procedures for these AI-driven pipelines to ensure their institutional interoperability and regulatory acceptance (Shahriari et al., 2025).

CONCLUSION

The results of this study showed that MRI and CT radiomics could be useful to predict the recurrence of cholesteatoma and surgical complexity in patients with chronic otological disease. The proposed framework identified and quantified imaging features from the preoperative scan that captured clinically relevant patterns including the extent of lesions, tissue heterogeneity, bone erosion, mastoid involvement and damage to the middle ear structures. Combination of radiomic features and machine learning algorithms led to effective risk stratification and enhanced prediction of postoperative recurrence and predicted surgical difficulty. The results indicate that ensemble-based models, such as Random Forest, Gradient Boosting and XGBoost, are appropriate models to model complex radiological patterns related to the behavior of cholesteatoma. Recurrence and operativeness were predicted by the features which were relevant, such as the findings of ossicular erosion, destruction of the scutum, lesion texture, diffusion restriction, mastoid opacification, and disease extension, identified by the feature importance findings. These imaging biomarkers can aid the surgeon in predicting the most challenging surgical scenarios, in choosing an operative strategy and in planning for more intensive follow-up care for patients who are at higher risk of recurrence. In conclusion, the proposed MRI and CT-based radiomics framework is a promising decision-supportive tool for personalized management of cholesteatoma. The use of the device could enhance pre-operative planning, minimize unexpected surgical difficulties and enable focused postoperative monitoring. The framework should be further validated with larger multicenter data sets, standardized imaging protocols, external validation cohorts and longitudinal follow-up data to substantiate its reliability and generalizability in routine otologic practice.

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