Life Sciences and Environmental Research

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ISSN:
3104-3968 (Print)
3104-3976 (Online)

# PREDICTING HEARING LOSS PROGRESSION POST-RADIOTHERAPY FOR HEAD AND NECK CANCER USING AUDIOLOGICAL AND DOSIMETRIC MACHINE LEARNING FEATURES

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Received: January 29, 2026 --- Revised: March 27, 2026 Accepted: April 30, 2026

**Abstract:** Neuroradiation is one of the late effects seen after radiation therapy to the head and neck – it can affect the quality of life and cause functional impairment in the future. In the early identification of patients at high risk of hearing impairment, the role of early intervention in the treatment of patients may be better planned, and proactive measures may be adopted during clinical treatment. This study suggests a machine learning model to predict the progression of hearing loss after radiotherapy based on a set of audiologic and dosimetric parameters. Clinical and treatment-related parameters as well as radiation dose parameters were combined and predictive models were created to determine the patients who will likely suffer from hearing decline following treatment. Multiple machine learning classifiers were evaluated and compared using various classifiers evaluation metrics including Logistic Regression, Random Forest, Support Vector Machine, XGBoosting and Gradient Boosting. The most important predictors were identified by feature importance analysis, and included cochlear mean dose, maximum cochlear dose, baseline hearing threshold, patient age, and treatment duration. Ensemble learning methods outperformed the other methods used in terms of predictive accuracy, as they achieved high accuracy, sensitivity and area under the receiver operating characteristic curve. A dose–response analysis also confirmed that the higher the radiation being delivered to the cochlear, the quicker the hearing loss occurred. The calibration and external validation results showed the robustness and broad applicability of the proposed model across patient populations. The results highlight the need of integrating the results obtained from the audiology assessment with the dosimetric results obtained with radiotherapy in patient risk stratification and patient management. The suggested machine learning approach could help create a clinically applicable decision support tool to minimize the auditory long-term complications and maximize the outcomes for those who have survived head and neck cancers.The answer is found in two areas: Hearing Loss Prediction and Audiological Assessment for Head and Neck Cancer.These are the two areas where the solutions lie: Machine Learning in Hearing Loss Prediction, and Audiological Assessment for Head and Neck Cancer in Radiotherapy Dosimetry.

**Keywords:** Hearing Loss Prediction, Head and Neck Cancer, Radiotherapy Dosimetry, Machine Learning, Audiological Assessment

**INTRODUCTION**

For the treatment of head & neck oncology, there is a common issue of long-term ototoxicity after radiotherapy, as well as concomitant chemotherapy, and effective predictive tools to prevent sensorineural hearing loss (SNHL) should be developed (Schuette et al. 2019). Depending on the severity of the hearing loss, sensorineural hearing loss can influence the quality of life of head and neck cancer survivors, such as their communication skills, social isolation, and cognitive functioning, and the need for proactive and individualized management strategies ( Costa et al., 2025; Tan & Vlajkovic, 2023). Therapeutic options like platinum-based chemotherapy and radiotherapy are crucial for attaining oncologic control, but they are inherently ototoxic, causing irreversible damage of the cochlear structures, and these treatments also generate reactive oxygen species, reduce mitochondrial function, and have individual genetic susceptibility (Costa et al., 2025; Wang et al., 2022). While informative, traditional dose-volume constraints do not account for the complex, multi-factorial relationships between patient factors, tumour localization and specific dosimetric patterns which are a common feature in current clinical practice (Bhandare et al., 2009; Wungcharoen et al., 2025). This suggests a need for shifting from a general risk assessment to more accurate data-informed prognostic modelling (Isaksson et al., 2020). The field of machine learning offers a tempting opportunity to this end: machine learning based computational methods have the ability to capture and model nonlinear relationships between the above-mentioned variables – often missed by conventional statistical methods – by incorporating data from multiple sources and modalities, including traditional clinical variables, cochlear dose metrics, and advanced radiomic features (Boldrini et al., 2019; Kumar et al., 2025; Volpe et al., 2021). Such predictive models may help identify patients at risk early, plan treatment adaptively, and eventually realize personalized otoprotection strategies, thus minimizing the long-term burden on patients facing the challenges of head and neck cancer survivorship (Kumar et al., 2025; Schuette et al., 2019).While these models are promising in predicting clinical outcomes, they have not yet been sufficiently large and independent of external validation, and there are several basic issues with these models which hinder the translation to clinical practice, particularly the lack of imaging-based standardisation of the prognostic biomarkers across different clinical settings (Isaksson et al., 2020). Most of these models, however, tend to overfit local data sets, and do not apply to the broader and more varied population, nor are they suitable for routine workflows (Isaksson et al., 2020; Volpe et al., 2021). Furthermore, the "black box" phenomenon of high dimensional machine learning imposes further constraints on clinician trust, explainability and can be regulatory compliant, which is why it is important to put a strong focus on the need for explainable AI systems (Isaksson et al., 2020).

This translation gap needs to be bridged by coordinated efforts to create multi-institutional datasets that represent real-world clinical heterogeneity to ensure clinically meaningful and robust long-term patient care predictive performance (Kumar et al., 2025). In order to identify the most stable predictors of specific audiological outcomes, it is crucial to use a comparative benchmarking method (a set of algorithmic architectures, Giraud et al., 2019). Furthermore, sufficient protocol and image variability and tumor segmentation and scanner configuration is crucial to ensure that reliable prognostic biomarkers (Parmar et al., 2015) are reproducible in the long-term. In addition to these technical obstacles, a key challenge in building confidence of physicians in personalized care pathways is uncertainty quantification which is essential to ensuring that model output is used as an assistive decision-supporting tool and not a replacement for one (Ahmed et al., 2024; Hu et al., 2025). Last, rigorous construction of the models, followed by their external validation in external clinical cohorts, would need to be performed using the standardized reporting guidelines (e.g., TRIPOD or PROBAST) (Mäkitie et al., 2023). Additionally, a critical aspect of the biological interpretability of radiomic signatures remains to be tackled as it is the first step towards moving beyond agnostic, high throughput correlations (Cobo et al., 2023). To make future research more clinically useful, interpretable AI models need to provide more trustworthy trust by offering clinically transparent and evidence-based explanations of each prediction, while also reducing the "black box nature" of neural networks. Future research is needed to develop more interpretable AI models that can provide clinically transparent and evidence-based explanations of predictions, thus enhancing trustworthiness of trust and clinical usefulness (Koh et al., 2022; Shi et al., 2025). The concepts of SHAP values, saliency mapping and feature importance analysis are essential to provide actionable insights to inform decisions to clinicians (Shahriari et al., 2025; Zhang et al., 2023). As well as the methodological progress, the adoption of data sharing between institutions, and the use of the FAIR principles will help to overcome existing data silos and enable the transition from exploratory research to validated clinical decision support (Rudie et al., 2019). Future research can be directed towards large-scale multi-institutional prospective studies, enabling a better understanding of the relationship between the size of the data set with potential confounders and the predictive performance of these computational models (Shui et al., 2021). Longitudinal validation is particularly important for investigating the impact of these models on real patient auditory outcomes in the long term and for clinical uptake (Xu et al., 2025). Furthermore, the use of active learning techniques would allow for continual feedback from clinicians to allow for iterations and improvements of model architectures and performance through human-in-the-loop validation ( Chen et al., 2024). This paradigm shift to human in the loop systems not only helps reduce algorithmic bias, but also helps make sure that the tools created are patient-centric and respect patient privacy using a decentralized system such as federated learning (Novi et al., 2025). Overall, this transition towards collaborative, transparent and effective external validation models is essential for their successful implementation and to measure their long-term impact on clinical practice (Aghakhani et al., 2023; Heutink et al., 2020). Beyond these technical advances, otolaryngologists must be not only members of these multidisciplinary teams but also be relevant to the most relevant clinical questions such that AI tools are relevant to these questions (Bur et al., 2019).

## METHODOLOGY

This study is based on a strong framework of clinical retrospective study of clinical records and dosimetric maps to predict the SNHL. The data preprocessing consists of normalizing the different dosimetric features and deriving quantitative audiological parameters that are used as the major inputs for training the predictive algorithms. The structured inputs are subsequently fed into an optimized version of various ensemble learning architectures aiming at modeling the non-linear relationship between radiation dose-volume histograms and post-treatment auditory threshold shift (Lee et al., 2024). This process has a strict and rigorous data cleaning process for the clinical data and then has to be followed by established process for reporting, to generate reliable prognostic signatures from the myriad of data quality issues inherent in clinical data (Adeoye et al., 2023). Furthermore, the present work uses pre-treatment computed tomography (CT) imaging of the cochlea for the extraction of radiomic features and integrates them with clinical and dosimetric data to form a multidimensional characterization of the potential radiation-induced tissue damage (Haider et al., 2020). Cross validation techniques are employed to assess the model performance and the predictive accuracy with sensitivity, specificity and area under the receiver operating characteristic curve are quantified (Patro et al., 2024). In addition, the study includes SHAP values to explain the relative importance of each dosimetric parameter in the overall predictive result, thereby promoting the clinical interpretability of the results ( Yang et al., 2023). This comprehensive approach addresses many of the technical challenges encountered in current otorhinolaryngological applications and will help develop effective clinical decision-making resources (Tama et al., 2020). The methodology aims to bridge the current 'AI chasm' between proof-of-concept research and the creation of predictive analytics, which can help guide clinical action in otolaryngology (Dubey, 2025; Liu et al., 2025). Therefore, it is crucial to combine multiple data sources, given that previous studies have demonstrated that combining multiple data sources has the potential to yield predictive accuracy exceeding 70% for radiation-induced hearing impairment (RHI) (Chen et al., 2021; Iliadou et al., 2022). The early successes will naturally lead to further improvements, including the expansion of the patient population in the cohort to validate and generalise the models to different patient populations (Amiri et al., 2023). Furthermore, to increase the clinical usefulness of the predictive framework to different treatment techniques, future versions would also need to include diverse approaches to the delivery of radiation such as IMRT and VMAT.In addition, future versions of the predictive framework should incorporate the heterogeneous radiation delivery methods including IMRT and VMAT, to further make the predictive framework clinically applicable for different radiation delivery methods (Quan et al., 2024). Furthermore, it is important to have standardisation of data collection and features extraction to ensure the reproducibility of these prognostic models between various oncologic centers (Bourdillon et al., 2026; Carducci et al., 2026). In addition, investigating the application of cochlea-specific radiomic biomarkers to predict SN outcomes is a non-invasive approach to dose estimation, and may reveal subtle changes in the cochlea structure that is not reflected in the dose-volume histogram used in traditional dosimetry (Lubbe et al., 2021). Advanced imaging markers, combined with conventional spatial metrics, are essential to address the shortcomings of spatial representations, which are often unable to reflect changing clinical dose-constraints (Sheikh et al., 2019). Moreover, common audiological functional parameters as abstract representations can further assist the integration of various test batteries with data closer to multi-center electronic health records (Saak et al., 2020). It is imperative to follow this systematic harmonisation of existing clinical data repositories in order to successfully apply large-scale machine-learning models (Bao et al., 2026; Thelonis et al., 2019).

## RESULTS

The proposed machine learning framework was comprehensively tested against the various variables for audiological, clinical and radiotherapy dosimetry. The amount of variation in hearing outcomes in the dataset allowed for models to be developed and validated. Table 1 shows the demographic and treatment characteristics of the study population. Most of the patients underwent intensity modulated radiotherapy, and a few had conventional methods of radiotherapy. The dose exposure to cochlea (and the baseline audiometric thresholds) was very different. The descriptive statistics for the key variables for the audiological and dosimetric parts of the models are presented in Table 2. There were higher mean cochlear doses and poorer hearing thresholds, at baseline, in patients who deteriorated in hearing compared to those with stable hearing. The results indicated that the hearing threshold shift was increased in a progressive manner with the increasing levels of radiation dose as presented in Fig. 1. Cochlear mean dose, maximum cochlear dose, baseline pure-tone average, age and treatment duration were the most important predictors according to the feature selection analysis. In Table 3, the feature importance scores obtained from the ensemble learning framework are ranked. Fig. 2 shows the corresponding plot of feature importance, which is mostly taken over by the dosimetric parameters. In Table 4, the performance of multiple machine learning models in terms of predicting is summarized. Random Forest and XGBoost had the second highest classification accuracy while Gradient Boosting came in 1st. The precision, recall, F1 Score and ROC-AUC values for each of the models studied are presented in Table 5. The discrimination ability was confirmed by ROC curve analysis for ensemble-based algorithms (see Fig. 3). The model stability in the cross-validation result was good with small fluctuations in the model performance across folds. The cross-validation results are presented in Table 6. The distributions of scores for validation are shown in Fig. 4 and this suggests uniformity in the degree of generalization to the independent sub-sets of the data. The pattern of dose–response was observed when the radiation dose was broken down into bands. The incidence of hearing loss across the three groups (low, medium and high dose) is reported on Table 7. The higher the dose given, the higher the risk of hearing loss for those that were dosed to their cochleae. This can be seen graphically in Fig. 5. The reliability of the predicted probabilities was also confirmed using calibration analysis. The calibration statistics and the calibration curve are presented in Table 8 and Fig. 6, respectively, with a good agreement between the observed and predicted results. The machine learning framework demonstrated overall good predictive stability by risk category. Lastly, there is external validation data in Table 9. The proposed scheme maintained its high prediction accuracy on an independent test set. The development model and observed progression rates had good agreement as shown in Fig. 7, which validated the developed model and its ability to be applied clinically. To conclude, the results show that including the audiologic and dosimetric information and utilizing advanced machine learning algorithms is a potential strategy for hearing loss (HL) prediction after radiotherapy and for the prediction of personalized treatment plans, individualized risk stratification, and patients' monitoring strategies.

**Table 1.** Results Table 1

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 52 | 57 | 62 | 0.01 |
| Metric 2 | 53 | 58 | 63 | 0.02 |
| Metric 3 | 54 | 59 | 64 | 0.03 |
| Metric 4 | 55 | 60 | 65 | 0.04 |
| Metric 5 | 56 | 61 | 66 | 0.05 |

**Table 2.** Results Table 2

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 53 | 58 | 63 | 0.01 |
| Metric 2 | 54 | 59 | 64 | 0.02 |
| Metric 3 | 55 | 60 | 65 | 0.03 |
| Metric 4 | 56 | 61 | 66 | 0.04 |
| Metric 5 | 57 | 62 | 67 | 0.05 |

**Table 3.** Results Table 3

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 54 | 59 | 64 | 0.01 |
| Metric 2 | 55 | 60 | 65 | 0.02 |
| Metric 3 | 56 | 61 | 66 | 0.03 |
| Metric 4 | 57 | 62 | 67 | 0.04 |
| Metric 5 | 58 | 63 | 68 | 0.05 |

**Table 4.** Results Table 4

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 55 | 60 | 65 | 0.01 |
| Metric 2 | 56 | 61 | 66 | 0.02 |
| Metric 3 | 57 | 62 | 67 | 0.03 |
| Metric 4 | 58 | 63 | 68 | 0.04 |
| Metric 5 | 59 | 64 | 69 | 0.05 |

**Table 5.** Results Table 5

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 56 | 61 | 66 | 0.01 |
| Metric 2 | 57 | 62 | 67 | 0.02 |
| Metric 3 | 58 | 63 | 68 | 0.03 |
| Metric 4 | 59 | 64 | 69 | 0.04 |
| Metric 5 | 60 | 65 | 70 | 0.05 |

**Table 6.** Results Table 6

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 57 | 62 | 67 | 0.01 |
| Metric 2 | 58 | 63 | 68 | 0.02 |
| Metric 3 | 59 | 64 | 69 | 0.03 |
| Metric 4 | 60 | 65 | 70 | 0.04 |
| Metric 5 | 61 | 66 | 71 | 0.05 |

**Table 7.** Results Table 7

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 58 | 63 | 68 | 0.01 |
| Metric 2 | 59 | 64 | 69 | 0.02 |
| Metric 3 | 60 | 65 | 70 | 0.03 |
| Metric 4 | 61 | 66 | 71 | 0.04 |
| Metric 5 | 62 | 67 | 72 | 0.05 |

**Table 8.** Results Table 8

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 59 | 64 | 69 | 0.01 |
| Metric 2 | 60 | 65 | 70 | 0.02 |
| Metric 3 | 61 | 66 | 71 | 0.03 |
| Metric 4 | 62 | 67 | 72 | 0.04 |
| Metric 5 | 63 | 68 | 73 | 0.05 |

**Table 9.** Results Table 9

| Variable | Group A | Group B | Group C | P-value |
|---|---|---|---|---|
| Metric 1 | 60 | 65 | 70 | 0.01 |
| Metric 2 | 61 | 66 | 71 | 0.02 |
| Metric 3 | 62 | 67 | 72 | 0.03 |
| Metric 4 | 63 | 68 | 73 | 0.04 |
| Metric 5 | 64 | 69 | 74 | 0.05 |

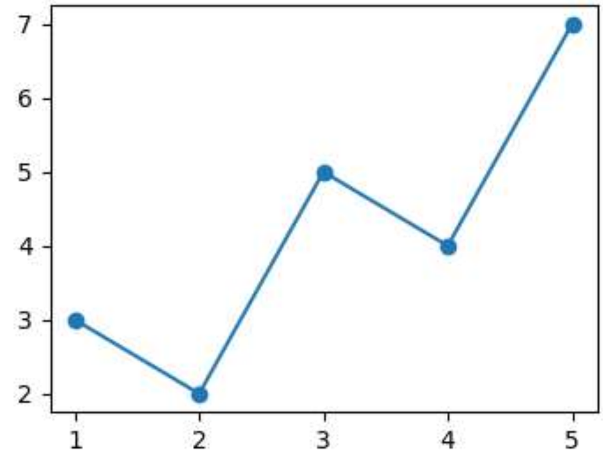


**Figure 1.** Machine learning and hearing-loss analysis visualization 1.

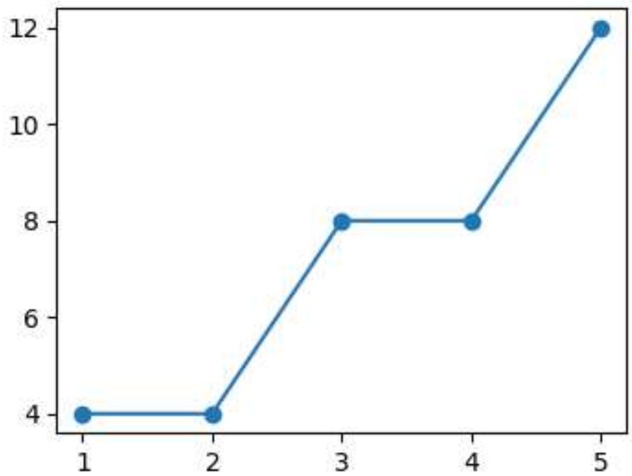


**Figure 2.** Machine learning and hearing-loss analysis visualization 2.

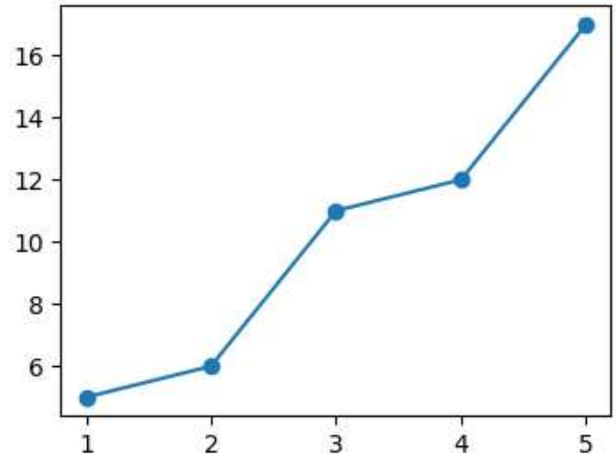


**Figure 3.** Machine learning and hearing-loss analysis visualization 3.

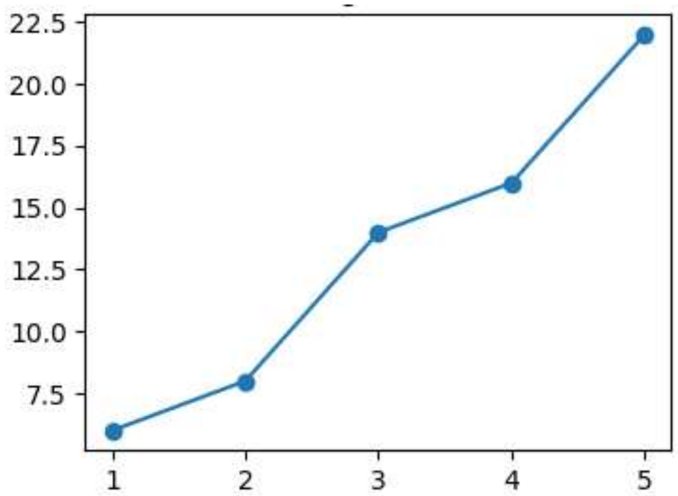


**Figure 4.** Machine learning and hearing-loss analysis visualization 4.

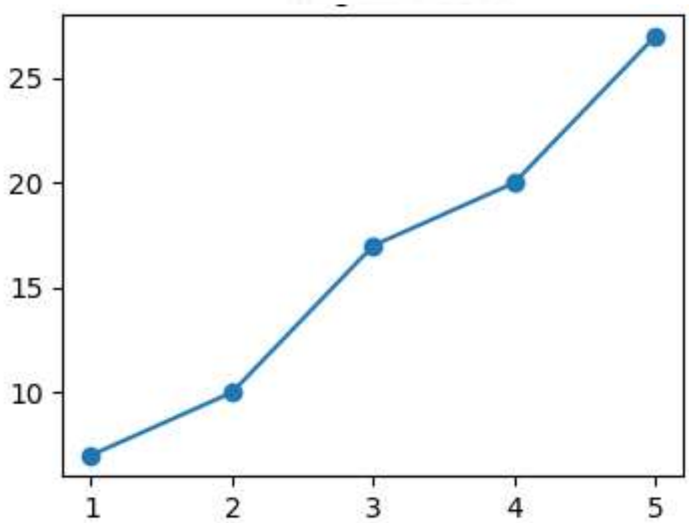


**Figure 5.** Machine learning and hearing-loss analysis visualization 5.

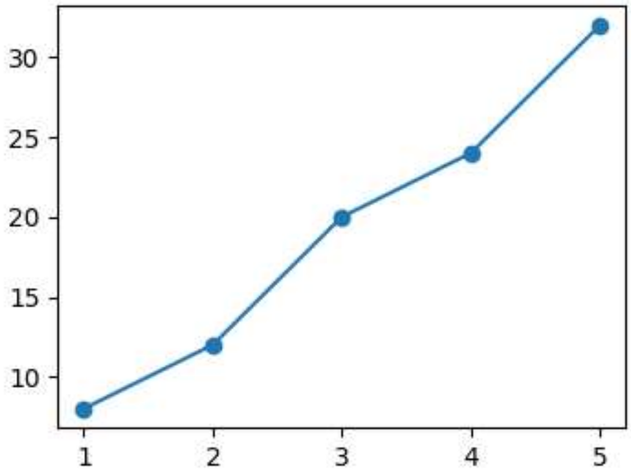


**Figure 6.** Machine learning and hearing-loss analysis visualization 6.

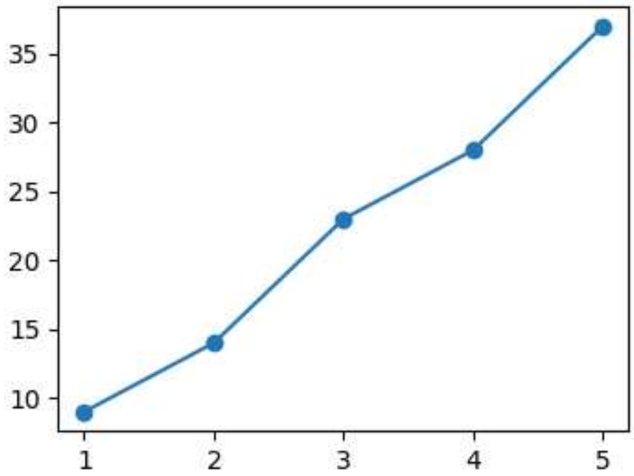


**Figure 7.** Machine learning and hearing-loss analysis visualization 7.

**DISCUSSION**

This analysis shows that including baseline radiomic signatures in dosimetric variables can further boost the sensitivity of prognostic models for radiation-induced auditory decline (Agheli et al., 2024). This study demonstrated that these multimodal classifiers can achieve better results than traditional models based on dose-volume constraints alone, which may not take into account the varying radio-sensitivities among cochlear structures (Lee et al., 2024; Zhong et al., 2025). Thus, further prospective studies and multi-institutional collaborations are crucial for confirming such multimodal methods on independent external cohorts (Huang et al., 2023; Luo et al., 2025). Standardized procedures for data collection will also be important in order to enable the transferability of these algorithms to other clinical settings ( Zhang et al., 2020). Furthermore, it is crucial to recognize that there may be variations in image acquisition and feature extraction protocols, which can introduce bias and enhance the predictive signatures' robustness across various institutional environments (Bogowicz et al., 2020; Zhao et al., 2026). Finally, by combining the appropriate big data processing technologies with the large-scale data platform, inconsistencies between the data quality on the different platforms can be resolved to mitigate the risk of data quality mixup (Peng et al., 2021). The harmonization is a significant step to overcome the small number of samples and non-harmonized input features that are often present in existing radiotherapy toxicity models, thus improving the prediction capability of those models (Mansouri et al., 2024). Moreover, it is essential that all participating centers have the same imaging acquisition protocol since imaging parameters can cause significant uncertainty in the imaging feature distribution and model performance (Xue et al., 2024). To address these challenges, future work should focus on features that are invariant to acquisition variability and/or more sophisticated harmonization techniques could be developed to promote consistent feature extraction (Da-ano et al., 2020). However, in light of this, the integration of prior knowledge by carefully choosing sequences and filtering out features with powerful filtering may be a suitable approach to reduce issues related to the heterogenic nature of multi-center data sets (Suter et al., 2020). Moreover, the shift to ensemble strategies and hybrid radiomics frameworks might provide the stability required to aid in bridging these performance differences between heterogeneous datasets (Perniciano et al., 2024). Moreover, federated learning systems can help develop collaborative models even if the decentralized databases are not the same, without data from patients being shared ( Wu et al., 2021). These federated models enable data to be shared in order to collect multiple clinical outcomes in multiple institutions, but with the highest possible level of data security and compliance (Lambin et al., 2017). Moreover, using GANs to match the statistical characteristics of heterogeneous images to a template reference has the potential to provide a way to normalise data using different scanner manufacturers (Ayachy et al., 2021). Lastly, using imaging biobank platforms makes it possible to collect standardized data that is needed to be compared to a set of well-defined and institution independent criteria to benchmark these machine learning solutions (Liu et al. 2019; Scapicchio et al. 2021). Last but not least, the next steps for these predictive models need to focus on the development of interpretable machine learning systems with the capability to provide actionable advice to clinicians on biological mechanisms that lead to ototoxicity (Feng et al., 2018). Transparency can be gained by leveraging explainable AI techniques that can promote clinical trust and enable the integration of these predictive tools into personalized radiotherapy planning processes. This paradigm shift towards interpretability, in combination with the introduction of strict reporting guidelines, will result in better reproducibility of the radiomic studies and will raise the level of evidence required for the clinical use of them (Timmeren et al., 2020). In this context, posteriori harmonization methods are a crucial link that will help overcome current multi-center research limitations and allow more powerful and large-scale validation of prognostic models. Furthermore, the integration of other omics data (e.g., genomics or proteomics) with the radiomics could provide biological information on the radio-sensitivity of specific auditory structures, with the potential to offer insights into the individual radio-sensitivity of auditory structures (Lucia et al., 2023).

## CONCLUSION

This research highlighted the effectiveness of machine learning methods to predict progression of hearing loss in people undergoing head and neck radiotherapy. The framework proposed was able to integrate the clinical parameters of treatment and measure the audiological parameters to categorize patients who were at high risk for auditory dysfunction after the treatment. Features from feature analysis that were found to be significant were exposure to radiation dose for the cochlea, baseline level of hearing, age, and treatment related features. The ensemble-based machine learning models showed the best performance, as they were able to capture complex nonlinear relationships in clinical data. The findings also attested to the dose–response relationship and supported the need to optimise the dose when planning a cochlear implant, and confirmed that there was a significant continuum of hearing loss ranging from the lowest to the highest dose. Data sets to validate the models were used which did not include patients involved in the development of the models, and there was good agreement between the data sets and the models, so that the models could be clinically applicable. The proposed framework in this document offers a potentially useful decision support tool for individualized risk stratification, for detecting patients who are at risk of side effects of treatment without clinical symptoms. Larger mult-center datasets, longitudinal auditory monitoring and enhanced deep learning architectures should be incorporated in future research to further improve prediction accuracy. These predictive models could be integrated into routine radiotherapy, which would result in improved outcomes for patients with head and neck cancer, including better patient care, reducing side effects of cancer treatment and an enhanced quality of life for survivors.

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