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Performance of artificial intelligence-based algorithms to predict prolonged length of stay after head and neck cancer surgery

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A R T I C L E I N F O

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A B S T R A C T

Background: Medical resource management can be improved by assessing the likelihood of prolonged length of stay (LOS) for head and neck cancer surgery patients. The objective of this study was to develop predictive models that could be used to determine whether a patient's LOS after cancer surgery falls within the normal range of the cohort.
Methods: We conducted a retrospective analysis of a dataset consisting of 300 consecutive patients who underwent head and neck cancer surgery between 2017 and 2022 at a single university medical center. Prolonged LOS was defined as LOS exceeding the 75th percentile of the cohort. Feature importance analysis was performed to evaluate the most important predictors for prolonged LOS. We then constructed 7 machine learning and deep learning algorithms for the prediction modeling of prolonged LOS.
Results: The algorithms reached accuracy values of 75.40 (radial basis function neural network) to 97.92 (Random Trees) for the training set and 64.90 (multilayer perceptron neural network) to 84.14 (Random Trees) for the testing set. The leading parameters predicting prolonged LOS were operation time, ischemia time, the graft used, the ASA score, the intensive care stay, and the pathological stages. The results revealed that patients who had a higher number of harvested lymph nodes (LN) had a lower probability of recurrence but also a greater LOS. However, patients with prolonged LOS were also at greater risk of recurrence, particularly when fewer (LN) were extracted. Further, LOS was more strongly correlated with the overall number of extracted lymph nodes than with the number of positive lymph nodes or the ratio of positive to overall extracted lymph nodes, indicating that particularly unnecessary lymph node extraction might be associated with prolonged LOS.
Conclusions: The results emphasize the need for a closer follow-up of patients who experience prolonged LOS. Prospective trials are warranted to validate the present results.

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1. Background

Head and neck squamous cell carcinomas (HNSCCs) originate in the mucosal epithelium of the head and neck area (Fig. 1). The cause of this disease varies within the different regions and has a high correlation to tobacco and alcohol consumption. New entities arise from colonization with high-risk human papillomavirus (HPV). The leading subtypes are HPV 16 and 18 [1–3].

HNSCC are the most common tumors in oral and maxillofacial surgery [4]. In most cases, these patients require extensive surgical and adjuvant therapy, which in most cases includes reconstruction with microvascular grafts followed by adjuvant radiation or chemotherapy combined with radiation, commonly known as chemoradiotherapy (CRT) [4]. CRT has established itself as a first-line therapy for tumors that develop in the pharynx or larynx [4]. As a rule, most HNSCC tumors require a multidisciplinary therapy concept. If possible, chemotherapy with cisplatin is to be favored in this clinical picture. Epidermal growth factor receptor antibodies (cetuximab) can be used in combination as sensitizers, for patients being ineligible for cisplatin [5]. Furthermore, immune checkpoint inhibitors such as pembrolizumab and nivolumab are used in the recurrent/metastatic setting of HNSCC tumors [6–8]. Besides these facts, oral cancer has a massive impact on quality of life regarding cosmetic appearance, psychological well-being, and the ability to participate in social interaction [9]. Due to its complexity, the treatment requires extensive staging in order to plan resection and reconstruction, to control possible complications of the operation and overall reduce the length of stay (LOS) [10].

An increase in healthcare costs has been accompanied by an improvement in the prognosis of head and neck tumors. Due to this correlation, a socioeconomic evaluation of the therapy is becoming increasingly important. From diagnosis to the start of treatment within the subsequent two years, it was shown that the costs of an advanced stage of the disease differed significantly. The authors' conclusion advocates a rapid therapeutic intervention for the patients to achieve a better prognosis as well as an economic relief of the health system [11]. An important parameter that must be taken into account when considering socioeconomic costs and surgical success is the actual LOS in the hospital. The LOS is regularly used to estimate and reduce hospital costs. From the patient's point of view, the LOS is also an essential parameter to evaluate the success of the intervention [12].

Artificial intelligence-based algorithms have the advantage of being able to efficiently investigate hidden patterns from very large amounts of data [13,14]. Its use for predicting patient outcomes based on various clinical variables has become increasingly popular [15–17]. By predicting clinical target variables, this method can significantly improve planning and treatment as well as improve healthcare resource allocations [18,19]. Various studies have already shown that certain features of tumor surgeries in the head and neck region are associated with an increased probability of complications and, consequently, a prolonged LOS. Factors such as alcohol consumption, longer operation time, greater intraoperative blood loss, and a more advanced TNM stage have been cited, along with various others [20]. In the field of head and neck tumor research, there are a number of clinically pathological features that can be used to determine whether a patient will have a longer LOS. One approach would be, for example, to anchor these algorithms within a digital hospital system, which would enable optimized digital archiving and continuous monitoring of patients who fulfill a certain risk profile to provide optimized treatment to them [12,21].

In the present work, various artificial intelligence-based algorithms were applied to predict LOS in patients with head and neck cancer. Furthermore, we investigated which variables contribute to this prediction process the most.

2. Methods

2.1. Study design and population

A retrospective design was used in this study. Its reporting complied with the TRIPOD statement [22] concerning the transparent reporting of multivariate prediction models and the "Strengthening The Reporting Of Observational Studies in Epidemiology

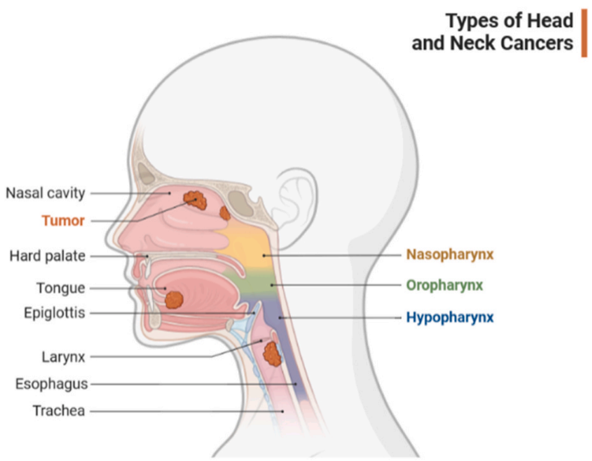

Fig. 1. Overview of the most common sites of manifestation of oral squamous cell carcinomas (HNSCC) (created with biorender.com).

(STROBE)" guidelines for observational studies [23]. At the Medical Center of the University of Wuerzburg, Germany, data from 300 patients were retrospectively examined. The examined time frame ranged from 2017 to 2022, and patients were consecutively included. Institutional review board approval was obtained (approval number 2022063001).

We assessed the eligibility of all adult patients who were treated in our clinic for histologically confirmed primary HNSCC in the above-mentioned period. As part of the inclusion criteria, patients with a primary tumor and undergoing primary surgery at our clinic were considered. Patients were excluded when presented with a recurrence or adjuvant therapy that had already taken place. Furthermore, patients who had been pretreated for cancer in other hospitals or patients outside the above-mentioned period were excluded.

2.2. Study measurements

Medical records were retrieved from patients' electronic medical records (EMRs). In order to identify the patient collective, the patients who were treated in our clinic were identified via the in-house medical control system on the basis of the clinic's organizational unit. Furthermore, a table was created using the ICD codes, which code the malignant neoplasm in the head and neck area. C01 up to C14.8, as well as the OPS codes 5-403-00 up to 5–403.05, which are codes for the neck dissection, were filtered. The table was prepared in pseudonymized form. The following parameters were collected: age, sex (male/female), body mass index (BMI), insurance type (private/general), inpatient stay start, inpatient stay end, intensive care stay, day of first diagnosis, therapy (surgery, chemotherapy/radiation, palliative care), day of surgery, day of last status (death, regression, progression, right censored), LOS, complication (yes/no), primary tumor, recurrence, second tumor), prior radiation (yes/no), operation time, American Society of Anesthesiologists risk classification score (ASA score), transplant/reconstruction (microvascular/local flap), clinical TNM classification, pathological TNM classification, number of lymph nodes and number of positive lymph nodes extracted, as well as ischemia time.

2.3. Statistical analyses

Statistical analyses were performed with SPSS modeler (v18.3, IBM Corp., Armonk, NY, USA), Python for Apache Spark framework within SPSS modeler and SPSS (v27, IBM Corp., Armonk, NY, USA). First, descriptive and explorative statistics were performed. Continuous variables are shown with mean and 95 % confidence intervals (95%CI) or median and range unless otherwise specified. Categorical variables are shown with counts and percentages. Binarization of LOS was performed by calculating the percentile ranks and binarizing them according to the 75th percentile. A feature importance analysis was performed to find the top predictors for prolonged LOS using the Chi-square automatic interaction detection (CHAID) tree-building node and Pearson chi-square to rank the importance values [24].

To overcome the problem of data imbalance (death cases were the minority class), we applied the Synthetic Minority Oversampling Technique (SMOTE) algorithm to the training dataset (k-neighbours: 5) [25]. The first step in the SMOTE algorithm is to select a minority class "a" instance at random and search for its k nearest minority class neighbours. To create the synthetic instance, one of the k nearest neighbours, "b", is selected at random and connected to "a" in the feature space to form a line segment. Synthetic instances are created by combining instances "a" and "b" in a convex fashion. The rationale behind this approach is that it provides new synthetic examples of the minority class that are plausible, i.e., that have similar features to existing examples of the minority group. In the process of constructing our machine learning models, we prioritized the importance of hyperparameter tuning. For this purpose, we incorporated the Rbfopt package within SPSS Modeler, an open-source software solution, to conduct the optimization. Rbfopt, employing Radial Basis Functions, helped in the systematic discovery of the optimal parameter set that resulted in the minimum possible error rate on our dataset. This approach ensured that every model utilized the best possible combination of parameters, aiding in error reduction and the overall enhancement of the models' predictive performance. This automated, systematic procedure facilitated a more efficient and accurate modeling process, leading to more robust predictions of the binary outcome under study. For the prediction models, we applied 5-fold cross-validation. Fifteen models were trained/tested, and the top models were chosen based on their Accuracy values. Among the final machine learning models were eXtreme Gradient Boosting (XGBoost), Lagrangian Support Vector Machine (LSVM), Random Trees, and Quick, Unbiased, Efficient Statistical Tree (Quest) [26,27]. Further, we trained two artificial neural network models: multiplayer layer perceptron (MLP-NN) and radial basis function neural network (RBF-NN). The models are characterized as follows:

1. XGBoost: XGBoost, or eXtreme Gradient Boosting, is an efficient algorithm that operates by constructing new models that predict the residuals or errors of prior models and then adds them together to make the final prediction. It uses a gradient boosting framework [28].
2. Lagrangian Support Vector Machine (LSVM): LSVM is a machine learning algorithm used for classification and regression analysis. It employs a strategy that attempts to find a hyperplane that maximally separates classes of data points [29].
3. Random Trees: Random Trees, a type of ensemble machine learning algorithm, build multiple decision trees and merge them together to get a more accurate and stable prediction [30].
4. Quick, Unbiased, Efficient Statistical Tree (Quest): Quest is a binary, non-parametric decision tree technique that selects the cut-off for splits based on statistical tests [31].

Additionally, we trained two artificial neural network models:

1. Multilayer Perceptron (MLP): MLP, a class of feedforward artificial neural network, consists of at least three layers of nodes [32].
2. Radial Basis Function Neural Network (RBF): RBF is a type of artificial neural network that uses radial basis functions as activation functions. It primarily uses a linear function in a high-dimensional nonlinear space [33].

The normal distribution of continuous variables was assessed with the Shapiro-Wilk-Test. Spearman's rank correlation was used for correlation analyses. *P*-values ≤ 0.05 were considered statistically significant.

3. Results

3.1. Descriptive statistics

All 300 patients (median [range] age, 65.00 [21–93] years; 176 [58.7 %] male) included in this analysis underwent surgery as primary therapy. A microvascular flap was used in n = 223 (74.3 %) of all cases, whereas a local flap was utilized in n = 77 (25.7 %) of all cases. The mean ± std BMI of patients was 26.02 ± 4.88. n = 250 (83.3 %) patients had public insurance and n = 50 (16.7 %) had private insurance. Mean operation time was 390 ± 166.82 min. The LOS ranged from 5 to 133 days (29.96 ± 15.75 days). LOS was further binarized based on the 75th percentile of the cohort to classify patients with prolonged LOS, resulting in n = 77 patients (25.7 %) with prolonged LOS and n = 223 (74.3 %) with LOS in the normal range. N = 16 patients (5.3 %) died following surgery. Recurrence of cancer was observed in n = 58 (19.3 %) of the cases. Table 1 shows the descriptive statistics of the cohort. Supplementary Table 1 provides detailed information regarding the cancer characteristics.

3.2. Important predictors for prolonged LOS

The results of the feature importance analysis are shown in Table 2. The leading parameters predicting prolonged LOS were operation time, ischemia time, the graft used, the ASA score, the intensive care stay, and the pathological stages. Other variables examined reached an importance score below 0.95.

Patients in the prolonged LOS group (Fig. 2) showed a higher number of removed lymph nodes. Further, patients in the LOS group were more likely to suffer recurrence when a smaller number of lymph nodes were extracted, indicating a need for closer follow-up in these patients. This was not seen in patients who did not have prolonged LOS. Consequently, these findings indicate that: 1)a higher number of lymph nodes resulted in a prolonged LOS but a lower risk of recurrence, and 2)a lower number of lymph nodes extracted in patients with prolonged LOS was associated with an increased probability of recurrence.

LOS was more strongly correlated with the overall number of extracted lymph nodes (Spearman's rho: 0.281; $p < 0.001$) than with the number of positive lymph nodes (Spearman's rho: 0.191; $p < 0.001$) or the ratio of positive to overall extracted lymph nodes (Spearman's rho: 0.174; $p < 0.001$), indicating that particularly unnecessary lymph node extraction might be associated with prolonged LOS.

3.3. Prediction modeling

The prediction modelling results using the top algorithms that achieved accuracy values of ≥ 0.6, with all features included, are shown in Table 3. For the training set, the Random Trees, XGBoost Tree, and LSVM models achieved the highest accuracies, while for the testing set, the highest accuracies were achieved by the Random Trees, LSVM, and Quest models.

We also carried out additional prediction modelling with only the most important features (as shown in Table 4), the results of

Table 1
Descriptive statistics of perioperative parameters and cancer outcomes. BMI: Body-Mass-Index; ASA: American Society of Anesthesiologists risk classification score. ICU stay: intensive care unit stay.

		Count (%)	Mean ± std
Sex	female	124 (41.3)	
	male	176 (58.7)	
Age			65 ± 12
BMI			26.02 ± 4.88
ASA Score	1	13 (4.3)	
	2	195 (65.0)	
	3	90 (30.0)	
	4	2 (0.7)	
Operation time			390.86 ± 166.82
Ischemia time			55 ± 34
Length of stay			21 ± 16
ICU stay			1 ± 1
Death	no	284 (94.7)	
	yes	16 (5.3)	
Recurrence	no	242 (80.7)	
	yes	58 (19.3)	

Table 2
Feature important analysis for the target variable prolonged length of stay. ASA: American Society of Anesthesiologists risk classification score. T: refers to the size or extent of the primary tumor; N: refers to the involvement of nearby lymph nodes; L: refers to the level of lymphatic invasion; Pn: refers to the presence or absence of perineural invasion.

Rank	Field	Measurement	Value
1	Operation time	Continuous	1.0
2	T	Nominal	1.0
3	Transplant	Nominal	1.0
4	Pn	Nominal	1.0
5	ASA Score	Ordinal	0.999
6	Age	Continuous	0.994
7	L	Nominal	0.993
8	ICU stay	Continuous	0.993
9	Ischemia time	Continuous	0.993
10	Number of Lymph nodes	Continuous	0.987
11	N	Nominal	0.984
12	Number of positive Lymph nodes	Continuous	0.957

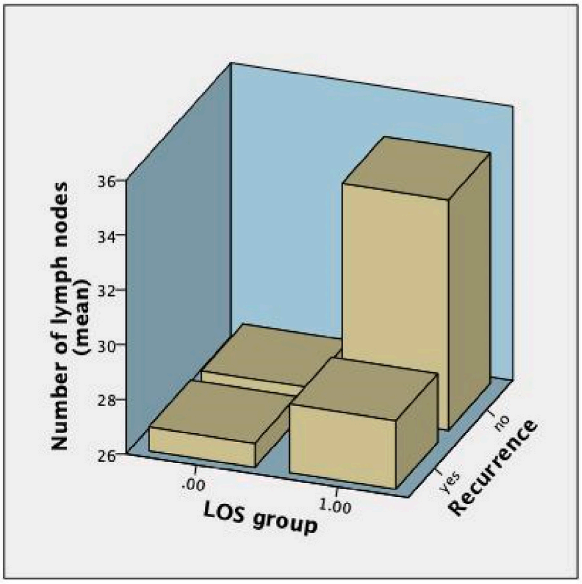

Fig. 2. Illustration of the impact of the number of lymph nodes extracted (mean) on length of stay (LOS), cancer recurrence, and death.

which are presented in Table 4. For the training set, the Random Trees, XGBoost Tree, LSVM, C&R Tree, and Quest models achieved the highest accuracies. For the testing set, the highest accuracies were achieved by the Random Trees, LSVM, Quest, C&R Tree, and XGBoost Linear models. Overall, the models incorporating only the most important features demonstrated superior performance compared to the models that included all features.

Fig. 3 (A-C) illustrates the model performance and feature importance of the best model obtained. The ROC curve for the Random Trees model trained with all features shows an AUC of 0.869. Notably, when the model was trained with only the most important features, the AUC increased substantially to 0.988. The feature importance plot demonstrates the contribution of individual features to the model's predictive ability when trained on the most important features only.

4. Discussion

HNSCC are the most common tumor entity in head and neck tumors [34]. Despite the significant decrease in tobacco-associated carcinomas in industrialized countries, the issue remains due to a substantial increase in human papillomavirus-associated carcinomas [34–36]. Since all these patients require a very complex therapy regime, it is of enormous interest to identify the high-risk patients among the total number who are at risk for prolonged LOS and thus require a greater therapeutic effort [37].

It is elementary to examine the different parameters, especially their interrelationship, to identify patterns that require an increased effort in diagnosis, treatment, and follow-up.

In the context of a lack of literature on identifying these patterns, we investigate whether prolonged LOS can be predicted from patient-specific data using artificial intelligence algorithms. One limitation is that large amounts of data are needed for a good

Table 3
Results of the prediction modeling with the top algorithms reaching accuracy values ≥ 0.7 for the prediction of LOS (all features). XGBoost: eXtreme Gradient Boosting; LSVM: Lagrangian Support Vector Machine; Quest: Random Trees, and Quick, Unbiased, Efficient Statistical Tree; C&R Tree: Classification and Regression (C&R) Tree; MLP-NN: multiplayer layer perceptron neural network; RBF-NN: radial basis function neural network.

Algorithm	Accuracy
Training	
Random Trees	95.24
XGBoost Tree	82.75
LSVM	78.26
C&R Tree	68.12
Quest	68.12
MLP-NN	76.90
RBF-NN	72.72
Testing	
Random Trees	81.23
LSVM	72.77
Quest	71.79
C&R Tree	71.45
XGBoost Linear	71.05
MLP-NN	64.79
RBF-NN	66.10

Table 4
Results of the prediction modeling with the most important features for the prediction of LOS (see Table 2 for most important features). XGBoost: eXtreme Gradient Boosting; LSVM: Lagrangian Support Vector Machine; Quest: Random Trees, and Quick, Unbiased, Efficient Statistical Tree; C&R Tree: Classification and Regression (C&R) Tree; MLP-NN: multiplayer layer perceptron neural network; RBF-NN: radial basis function neural network.

Algorithm	Accuracy
Training	
Random Trees	97.92
XGBoost Tree	84.38
LSVM	81.25
C&R Tree	81.25
Quest	78.13
MLP-NN	76.10
RBF-NN	75.40
Testing	
Random Trees	84.14
LSVM	75.32
Quest	75.31
C&R Tree	75.01
XGBoost Linear	74.06
MLP-NN	64.90
RBF-NN	66.70

evaluation [16,38]. Even though we could only use a limited number of patients for the analysis, our results show that LOS can be predicted adequately. Further, our results can serve as a basis for larger multicenter prospective studies that can develop more accurate models based on these initial results on a larger patient dataset. Another limitation is that the present data only included a German patient cohort from a single center. A comparison with other patient cohorts may therefore be limited [39]. The nature of retrospective studies also brings the limitation that other relevant data such as medications, compliance, and other parameters are not examined if these were not recorded and thus limit the final interpretation [13,39].

Notably, there are also numerous other algorithms that could be used for prediction modeling [39]. We used various types of machine learning and deep learning algorithms, including Random Trees, XGBoost Tree, LSVM, C&R Tree, Quest, MLP-NN, and RBF-NN, which each have unique strengths. These algorithms differ from a common convolutional neural network (CNN) in terms of

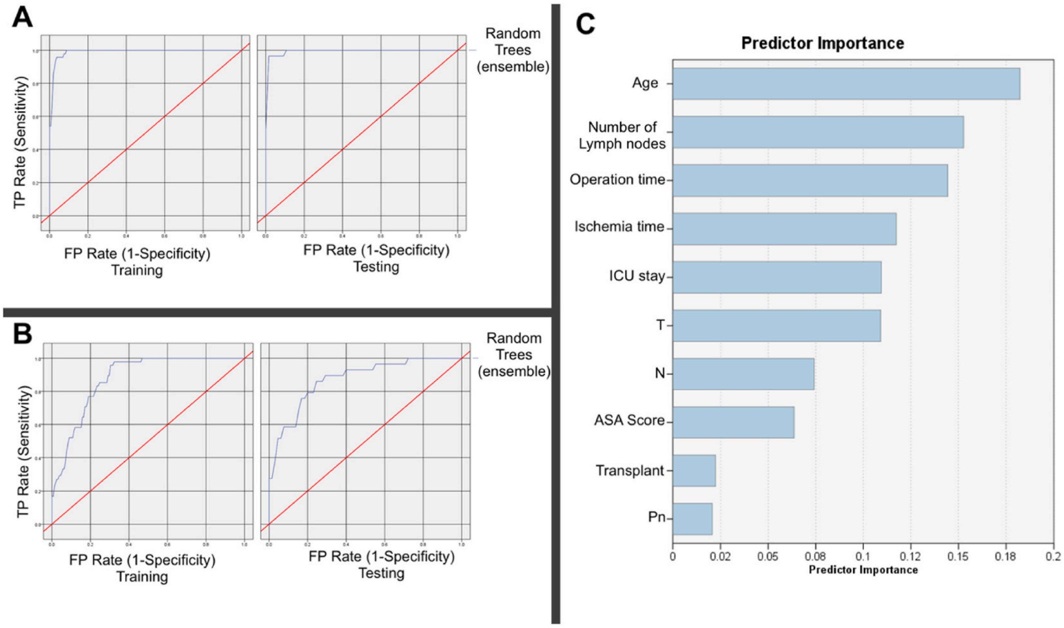

Fig. 3. Comparative Evaluation of Model Performance and Feature Importance. The figure presents (A) the ROC curve for the ensemble Random Trees model trained with only the most important features (AUC = 0.988), (B) the ROC curve for the ensemble Random Trees model trained with all features (AUC = 0.869), and (C) the feature importance plot from the ensemble Random Trees model trained with the most important features. The term "ensemble" denotes that the model was trained using ensemble methods in the auto classifier to improve predictive accuracy. ASA: American Society of Anesthesiologists risk classification score; ICU stay: intensive care unit stay; T: refers to the size or extent of the primary tumor; N: refers to the involvement of nearby lymph nodes; Pn: refers to the presence or absence of perineural invasion.

their structure and the way they learn. CNNs are typically used for image processing tasks, where they excel at recognizing patterns in 2D arrays of pixels due to their layered architecture. This is in contrast to the models we used, which are more typically employed for structured tabular data. Among the models we used, tree-based models such as Random Trees and XGBoost, create decision trees based on the input variables and make predictions based on the paths followed in the decision tree. Support Vector Machines (LSVM) work by finding the optimal boundary that separates the classes in the feature space. Artificial Neural Networks (MLP-NN and RBF-NN) mimic the structure of the human brain and are capable of learning complex, non-linear relationships. Each of these models have advantages. For example, tree-based models are easy to understand and interpret, and are less sensitive to outliers than regression-based models. Neural networks, meanwhile, are powerful and flexible, capable of learning complex relationships in the data, but may require more data and computational resources.

However, these algorithms also share the drawback of needing a certain number of cases for the learning process and an additional set for the evaluation process. The use of established statistical analysis, such as linear regression models, may be faster and more cost- and time efficient. Moreover, the metrics obtained from the algorithms depend highly on the feature included. Other datasets with different variables may produce different metrics, making a direct comparison in future studies difficult [39]. However, the feature set used in this study can be used to pave the way to accurate LOS prediction for future studies.

In the context of cancer prognosis, recent research conducted by Jo et al. incorporated the use of sophisticated machine learning techniques such as Extreme Gradient Boosting (XGB), Multilayer Perceptron (MLP), and Logistic Regression (LR) to predict prolonged length of stay (LOS) in various cancer types, including oral cancer [40]. They reported the AUCs of XGB, MLP, and LR as 0.67, 0.67, and 0.65 respectively, demonstrating the effectiveness of machine learning approaches in this predictive task. Interestingly, they concluded that models predicting LOS were more effective when a combination of preoperative data and intraoperative data was employed. This is congruent with our findings where the incorporation of these data types culminated in robust performance metrics. Specifically, they highlighted that models trained with preoperative variables and operative time generally superseded the models trained without operative time, which is consistent with our results, where operative time emerged as one of the most pivotal features.

Although literature specifically investigating the application of advanced techniques like machine learning or deep learning for predicting LOS in oral cancer patients based on intraoperative and preoperative features is relatively scarce, there exist numerous studies exploring algorithms to predict prolonged LOS in diverse other cancer entities and contexts. For instance, Masum et al. demonstrated that a Support Vector Machine model could predict LOS with an accuracy of 83.21 % in colorectal cancer patients [41]. This research identified age groups, ASA grade, and operation time as the foremost predictors for LOS prediction, reinforcing our findings. Interestingly, they also posited that BMI does not significantly contribute to LOS prediction, which aligns with our study where BMI did not rank within the top 12 predictors. However, one should exercise caution while comparing prolonged LOS across different cancer types, given that the types of surgery and model performance are contingent on diverse variable sets.

Our study, leveraging machine learning algorithms, has demonstrated a high predictive performance for LOS in HNSCC patients, with the Random Tree model delivering superior results. However, the external validation of these findings in a prospective setting is warranted, ideally incorporating the critical features identified in this study.

Due to the update of the TNM classification in 2017, we limited study period to the time frame between 2017 and 2022 to maintain compatibility with future studies. The main change within this update for oral squamous cell carcinoma is the depth of invasion as well as the HPV association. Here, more consideration is given to a thick, exophytic, but less invasive tumor as well as an ulcerative and deeply invasive tumor [42]. In a Japanese study, a clear downstaging could be described by applying the new classification [43]. With regard to the lymph nodes, it could be shown that patients with LN metastases and extracapsular spread have experienced an upstaging. In this context, the status of the removed LN during the neck dissection is increasingly evaluated as an important parameter for the prediction of the prognosis [44]. Under this assumption, we analyzed the number of positive and overall number of removed lymph nodes and their influence on the LOS Notably, the results showed that LOS is significantly associated with the absolute number of removed lymph nodes and less with the positive or the ratio of positive to the absolute number. Potentially unnecessarily removed lymph nodes can cause a prolonged LOS, as shown in our results. Although our results and the literature indicate that more removed lymph nodes result in a lower rate of recurrences, this side effect should be taken into account in the context of patient welfare [45]. Further, a lower number of lymph nodes extracted in patients with prolonged LOS was associated with an increased probability of recurrence, emphasizing the need for close follow-ups for these prolonged LOS risk patients. Overall, the results emphasize the need for better diagnostics pathways to detect positive lymph nodes before or during surgery.

Our cohort resembles the characteristics of head and neck cancer patients reported in the literature. It contained 124 females and 176 males, confirming previous findings that males might be more frequently affected due to significantly more pronounced risk factors [46]. The number of lymph nodes extracted in our study (mean: 28.35 lymph nodes) was comparable to values reported in other studies [45,47]. Using statistical models, previous work already described various predictive factors such as the advanced age of the patients, a higher ASA score, a prolonged operation time, and a prolonged ventilation time (which is associated with intensive care stay as included in our study) correlating to a prolonged stay [20,48]. In addition to other values recorded in the study described above, we were able to confirm the association for the described factors in the present work utilizing sophisticated artificial intelligence-based methods. The accuracy values ranged from 75.40 (RBF-NN) to 97.92 (Random Trees) for the examined AI models for the training set. Testing set accuracies were similar, with accuracy ranging from 64.90 (MLP-NN) to 84.14 (Random Trees). Validation of the algorithms with a higher number of patients that were prospectively examined could pave the way for implementation into a hospital documentation system and lead to improved patient care within the framework of daily rounds.

Operation time followed by T stage and transplant were shown to be leading predictors for LOS in our study. Parameters such as operation time, transplant, the ASA score, and age can be recorded directly after the operation to identify a patient at risk for prolonged LOS utilizing the provided algorithms. Similar methods have been already established in other surgical fields [49]. While our study provides valuable insights into predicting prolonged LOS after head and neck cancer surgery, it has some limitations. One of these is the lack of consideration of patient comorbidities, which can significantly impact the LOS. Although our models performed well with the included variables, comorbidities present a level of complexity and diversity that we felt our current sample size could not adequately address. Future studies with larger datasets and advanced modeling techniques could potentially incorporate comorbidities to enhance the prediction of prolonged LOS. Combination with other relevant parameters that are added during the course of the inpatient stay, such as the pathological findings and genetic markers, could lead to more precise multimodal data algorithms [16]. While we believe that our study makes valuable contributions to both the clinical and technical aspects of healthcare research, it is also important to acknowledge the limitations for potential implementations of the algorithms that arise from this interdisciplinary approach. On the technical side, it should be noted that while some machine learning models displayed promising results in predicting the prolonged LOS after head and neck cancer surgery, others did not perform as well. This variability underscores the necessity for further research to optimize algorithms and validates the importance of this study as a comparative assessment. Furthermore, the focus on a specific subset of head and neck cancer surgeries may limit the generalizability of our findings, pointing towards the need for broader studies that encompass a wider range of surgical procedures.

5. Conclusions

The presented algorithms could predict prolonged LOS in head and neck cancer patients with an accuracy of up to 97.92%. The leading variables for the prediction task were operation time, ischemia time, transplant, ASA score, intensive care stay, and TNM-stages. This might be caused by more extended tumor burden and more challenging resections and reconstructions. The results revealed that patients who had a higher number of harvested lymph nodes, had a lower probability of recurrence but also a greater LOS. However, patients with a prolonged LOS, especially when a lower number of lymph nodes were extracted, were also at greater risk for recurrence. Further, LOS was more strongly correlated with the overall number of extracted lymph nodes than with the number of positive lymph nodes or the ratio of positive to overall extracted lymph nodes, indicating that particularly unnecessary lymph node extraction might be associated with prolonged LOS. The results emphasize the need for a closer follow-up of patients who experience prolonged LOS.

Ethics approval and consent to participate

Institutional review board approval was obtained (approval number 2022063001) from the Medical Center of the University of Wuerzburg, Germany. The Institutional review board of the Medical Center of the University of Wuerzburg, Germany waived the necessity to retrospectively obtain consent of each of the patient included in this study due to the pseudonymization of patient data and the retrospective study design. No identifying data from patients were used in the statistical analyses.

Consent for publication

Not applicable.

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This research received no external funding.

Availability of data and materials

The raw data and algorithm structures analyzed during the current study are available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Andreas Vollmer: Conceptualization, Formal analysis, Validation, Writing – original draft. **Simon Nagler:** Data curation, Investigation, Writing – review & editing. **Marius Hörner:** Data curation, Investigation, Writing – review & editing. **Stefan Hartmann:** Conceptualization, Formal analysis, Supervision, Writing – review & editing. **Roman Brands:** Supervision, Writing – review & editing. **Niko Breitenbücher:** Data curation, Writing – review & editing, Resources. **Anton Straub:** Resources, Writing – review & editing. **Alexander Kübler:** Supervision, Writing – review & editing. **Michael Vollmer:** Formal analysis, Validation, Writing – review & editing. **Sebastian Gubik:** Formal analysis, Writing – review & editing. **Gernot Lang:** Data curation, Writing – review & editing. **Jakob Wollborn:** Formal analysis, Writing – review & editing. **Babak Saravi:** Conceptualization, Investigation, Methodology, Software, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e20752.

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