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Original Research Article

Development and Validation of a Machine Learning Model for Predicting Tympanoplasty Outcomes: A Retrospective Study

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Abstract:

Background: Tympanoplasty is a widely performed procedure for the surgical management of chronic otitis media with tympanic membrane perforation. Although graft success rates are generally high, hearing and anatomical outcomes remain variable and are influenced by multiple interacting clinical, audiological, and surgical factors. Machine learning (ML) models can integrate multiple preoperative variables to provide individualized outcome predictions that may outperform conventional scoring systems and regression-based approaches.

Objectives: To develop and internally validate machine learning models for predicting successful surgical and audiological outcomes following tympanoplasty, and to compare their performance with conventional logistic regression.

Methods: This retrospective cohort study was conducted in the Department of Otorhinolaryngology, ANMC, Gaya, and included 100 patients who underwent type I tympanoplasty with a minimum follow-up of 1 year. Preoperative demographic, audiological, and intraoperative variables were recorded. A successful outcome was defined as an intact tympanic membrane graft with a postoperative air-bone gap (ABG) of ≤20 dB at 1 year. Logistic regression, random forest, support vector machine, and k-nearest neighbor models were trained and validated using a stratified train-test split with 5-fold cross-validation. Model performance was assessed using accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC), and F1-score. Feature importance was derived from the best-performing model.

Results: Of 100 patients, 78 (78%) achieved a successful outcome at 1 year. The random forest model achieved the best discriminative performance (accuracy 0.87, AUC 0.89, 95% CI 0.81-0.96), outperforming logistic regression (AUC 0.81), support vector machine (AUC 0.84), and k-nearest neighbors (AUC 0.78). The most important predictors identified by the random forest model were preoperative air-bone gap, perforation size, Eustachian tube function, and graft material.

Conclusion: A random forest-based machine learning model demonstrated good discriminative ability for predicting tympanoplasty outcomes and outperformed traditional logistic regression in this cohort. Preoperative air-bone gap, perforation size, Eustachian tube function, and graft material were identified as the leading predictors. With external validation in larger cohorts, such models may assist clinicians in preoperative counselling and surgical planning.

Keywords: Tympanoplasty; Machine Learning; Random Forest; Predictive Model; Air-Bone Gap; Chronic Otitis Media.

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Introduction

Chronic otitis media (COM) is one of the most frequent otological disease in clinical practice and is a leading cause of conductive hearing loss and chronic ear discharge all over the world [1]. The surgical management of tympanic membrane perforations and restoration of the sound conducting mechanism of the middle ear is still the gold standard method, described by Zollner and Wullstein [2].

The success rate of tympanoplasty for an intact graft is in the range of 90% or higher [4]; however, functional hearing results are much more variable and reported success rates vary widely based on the definition of success used and the population studied, ranging from about 40% to 75% [2,3]. This disparity between graft uptake and hearing improvement underlines the multifaceted determinants of surgical results such as patient-related factors, including age, Eustachian tube function, and the condition of the other ear; disease-related factors, including the size and site of the perforation, middle ear mucosal condition, and active otorrhea; and surgical factors, including the type of graft material, surgical approach, and surgeon experience [3,4].

The Middle Ear Risk Index (MERI) and the Ossiculoplasty Outcome Parameter Staging (OOPS) index have been developed as scoring systems for stratifying the risk for middle ear surgery and predicting hearing outcomes after surgery [5]. These indices, however, are based on a few weighted variables and do not reflect all the non-linear and complex interactions among the various preoperative factors and surgical outcomes [6].

In contrast to traditional scoring systems and regression-based models, machine learning (ML) techniques have the potential to evaluate multiple variables and their interactions simultaneously, without requiring them to have specified linear relationships, thereby providing some advantage. In recent years, ML algorithms, such as the random forest, support vector machine and k-nearest neighbor classifiers, have been used to estimate the risk of complications after tympanoplasty and other otologic surgeries, the risk of developing an air-bone gap after surgery, and the likelihood of developing an air-bone gap after surgery. Most studies have found that the random forest model performs the best and provides better prediction accuracy than the traditional scoring systems and logistic regression [6,7]. Such an approach has also been used to predict the hearing recovery after a canal wall mastoidectomy with tympanoplasty and sudden sensorineural hearing loss, further confirming the feasibility of ML based prognostication in otology [8,9].

However, with the growing amount of evidence, predictive models for tympanoplasty outcomes using machine learning techniques are still under-explored in Indian tertiary care settings with potentially different patient demographics, chronicity of disease and access to resources compared to those of published cohorts [10]. Locally validated predictive tools could aid in more personalized counselling before the procedure, better identification of patients who require further preoperative optimization (e.g. Eustachian tube dysfunction treatment, dry period before surgery), and assist in the planning of the surgery, including the selection of graft material and the surgical approach [4,7].

Hence, this study was conducted to develop and validate machine learning models such as random forest, support vector machine, k-nearest neighbor, and logistic regression models to predict the outcomes of tympanoplasty following 1 year and to determine the key factors affecting the surgical and auditorial outcomes based on the model using the feature importance analysis technique.

Materials and Methods

Study Design and Setting: This retrospective cohort study was conducted in the Department of Otorhinolaryngology (ENT), Anugrah Narayan Magadh Medical College and Hospital (ANMC), Gaya, Bihar. Patients who underwent type I (underlay) tympanoplasty for chronic otitis media with a minimum postoperative follow-up of 1 year were identified from hospital records. Institutional Ethics Committee approval was obtained, and patient data were anonymized prior to analysis.

Sample Size: A total of 100 patients who fulfilled the inclusion and exclusion criteria and had complete preoperative, intraoperative, and 1-year follow-up data were included in the final analysis.

Inclusion Criteria

- Patients aged 12 years and above with a dry central or marginal tympanic membrane perforation due to chronic otitis media (mucosal, inactive type) undergoing primary type I tympanoplasty
- Availability of complete preoperative pure tone audiometry (PTA) and otoendoscopic findings
- Minimum postoperative follow-up of 1 year with documented graft status and PTA

Exclusion Criteria

- Cholesteatoma or active discharging ear at the time of surgery
- Ossiculoplasty or combined mastoidectomy procedures (type II-V tympanoplasty)
- Revision tympanoplasty cases
- Patients with sensorineural hearing loss as the predominant pathology, or incomplete records/lost to follow-up before 1 year

Variables Collected: The following preoperative and intraoperative variables were extracted for model development:

- Demographic: age, sex, smoking status, diabetes mellitus
- Audiological: preoperative air-bone gap (ABG) on pure tone audiometry
- Otoscopic/disease-related: perforation size (% of pars tensa), perforation site

(central/marginal), status of middle ear mucosa, Eustachian tube function (assessed clinically/by tympanometry), history of otorrhea within 3 months preoperatively, status of contralateral ear, duration of dry ear

- Surgical: graft material (temporalis fascia vs cartilage-perichondrium), surgical approach (endoscopic vs microscopic), surgeon experience

Outcome Definition: A successful outcome at 1 year was defined as a composite of (a) an intact, well-taken tympanic membrane graft on otoendoscopy, and (b) a postoperative air-bone gap of ≤20 dB on pure tone audiometry, in line with previously reported criteria for tympanoplasty success [3,4]. Patients not meeting both criteria were classified as having an unsuccessful outcome.

Machine Learning Model Development: Data were preprocessed by encoding categorical variables and standardizing continuous variables. The dataset was split into training (70%) and testing (30%) sets using stratified random sampling to preserve the outcome distribution. Four classification algorithms were trained: logistic regression (as a baseline comparator), random forest, support vector machine (radial basis function kernel), and k-nearest neighbors (k = 5). Hyperparameters were tuned using 5-fold cross-validation on the training set with grid search. Model performance on the held-out test set was evaluated using accuracy, sensitivity, specificity, F1-score, and the area under the receiver operating characteristic curve (AUC) with 95% confidence intervals derived using bootstrap resampling (1000 iterations). Feature importance for the best-performing model was computed using mean decrease in Gini impurity.

Statistical Analysis: Continuous variables were expressed as mean ± standard deviation (SD) and compared between outcome groups using the Student's t-test or Mann-Whitney U test as appropriate. Categorical variables were expressed as frequencies and percentages and compared using the Chi-square test or Fisher's exact test. A p-value of less than 0.05 was considered statistically significant. Statistical analysis was performed using Python (scikit-learn, pandas) and SPSS software (version 25.0 or equivalent).

Results

A total of 100 patients who underwent type I tympanoplasty and completed 1-year follow-up were included. Baseline demographic, audiological, and surgical characteristics are summarized in Table 1.

Table 1: Baseline characteristics of the study population (N = 100)

Variable	Value
Mean age (years), mean ± SD	32.4 ± 13.6
Male sex, n (%)	54 (54.0%)
Mean preoperative ABG (dB), mean ± SD	28.7 ± 8.4
Mean preoperative perforation size (%), mean ± SD	46.2 ± 18.1
Central perforation, n (%)	81 (81.0%)
Marginal perforation, n (%)	19 (19.0%)
Eustachian tube dysfunction, n (%)	27 (27.0%)
Active otorrhea within 3 months preop, n (%)	18 (18.0%)
Cartilage graft used, n (%)	37 (37.0%)
Temporalis fascia graft used, n (%)	63 (63.0%)
Endoscopic approach, n (%)	41 (41.0%)
Microscopic approach, n (%)	59 (59.0%)
Smokers, n (%)	14 (14.0%)
Diabetes mellitus, n (%)	11 (11.0%)

Surgical Outcomes: At 1-year follow-up, a successful outcome (intact graft with postoperative ABG ≤20 dB) was achieved in 78 of 100 patients (78%). Graft uptake alone (irrespective of hearing outcome) was achieved in 91 patients (91%), while 22 patients (22%) did not meet the composite success criterion, primarily due to a persistent air-bone gap >20 dB despite an intact graft (n = 14) or graft failure (n = 8).

Univariate Comparison of Predictors: Table 2 compares baseline characteristics between patients with successful and unsuccessful outcomes. Patients with unsuccessful outcomes were significantly older (38.1 ± 14.7 vs 30.8 ± 12.9 years, p = 0.024), had higher preoperative ABG (38.4 ± 6.9 vs 26.1 ± 7.2 dB, p < 0.001), larger perforations (63.6% ± 14.2% vs 41.5% ± 15.4%, p < 0.001), a higher proportion of marginal perforations (36.4% vs 14.1%, p = 0.018), Eustachian tube dysfunction (50.0% vs 20.5%, p = 0.006), recent otorrhea (36.4% vs 12.8%, p = 0.011), and were less likely to have received a cartilage graft (18.2% vs 42.3%, p = 0.043).

Table 2: Comparison of baseline variables between patients with successful and unsuccessful outcomes

Variable	Successful Outcome (n=78)	Unsuccessful Outcome (n=22)	p-value	Significance
Mean age (years), mean ± SD	30.8 ± 12.9	38.1 ± 14.7	0.024	*
Mean preoperative ABG (dB), mean ± SD	26.1 ± 7.2	38.4 ± 6.9	<0.001	*
Mean perforation size (%), mean ± SD	41.5 ± 15.4	63.6 ± 14.2	<0.001	*
Marginal perforation, n (%)	11 (14.1%)	8 (36.4%)	0.018	*
Eustachian tube dysfunction, n (%)	16 (20.5%)	11 (50.0%)	0.006	*
Active otorrhea within 3 months preop, n (%)	10 (12.8%)	8 (36.4%)	0.011	*
Cartilage graft, n (%)	33 (42.3%)	4 (18.2%)	0.043	*
Endoscopic approach, n (%)	35 (44.9%)	6 (27.3%)	0.146	
Smoking status, n (%)	9 (11.5%)	5 (22.7%)	0.171	

Machine Learning Model Performance: Table 3 summarizes the performance metrics of the four classification models on the held-out test set. The random forest model demonstrated the highest discriminative performance, with an accuracy of 0.87 and an AUC of 0.89 (95% CI 0.81-0.96), followed by the support vector machine (AUC 0.84), logistic regression (AUC 0.81), and k-nearest neighbors (AUC 0.78). Figure 1 shows the receiver operating characteristic (ROC) curves for the random forest and logistic regression models.

Table 3: Performance metrics of machine learning models on the test set

Model	Accuracy	Sensitivity	Specificity	AUC (95% CI)	F1-score
Logistic Regression	0.80	0.73	0.83	0.81 (0.71-0.90)	0.71
Random Forest	0.87	0.82	0.90	0.89 (0.81-0.96)	0.79
Support Vector Machine	0.83	0.77	0.85	0.84 (0.74-0.92)	0.74
k-Nearest Neighbors	0.78	0.68	0.82	0.78 (0.67-0.88)	0.67

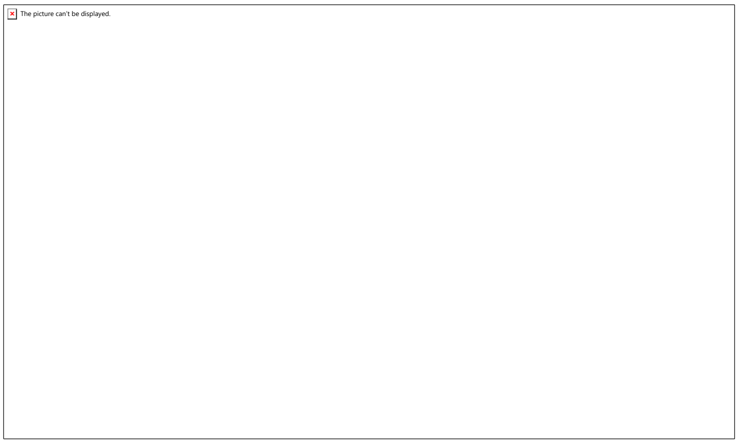

Figure 1. Receiver operating characteristic (ROC) curves comparing the random forest and logistic regression models for prediction of tympanoplasty outcome (illustrative data).

Feature Importance Analysis: Feature importance derived from the random forest model is presented in Table 4 and Figure 2. The four most important predictors of outcome were preoperative air-bone gap, perforation size, Eustachian tube function, and graft material, together accounting for approximately 60% of the total relative importance in the model.

Table 4: Relative feature importance from the random forest model

Rank	Predictor Variable	Relative Importance (Gini)
1	Preoperative air-bone gap (dB)	0.182
2	Perforation size (%)	0.156
3	Eustachian tube function	0.139
4	Graft material (cartilage vs fascia)	0.121
5	Status of contralateral ear	0.098
6	Middle ear mucosa status	0.092
7	Duration of dry ear (months)	0.081
8	Age	0.058

9	Surgical approach (endoscopic vs microscopic)	0.045
10	Smoking status	0.028

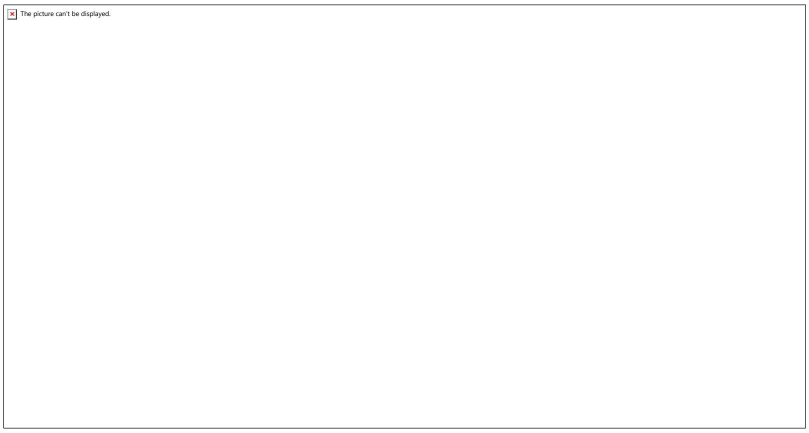

Figure 2: Relative feature importance (Gini importance) of the top 10 predictor variables in the random forest model (illustrative data).

Discussion

A composite successful outcome (intact graft with postoperative ABG ≤20 dB) was obtained in 78% of patients (100) in the present series of type I tympanoplasty at 1 year after surgery and graft uptake alone was obtained in 91% of patients (100). The random forest model outperformed the other machine learning models, with an AUC of 0.89 vs logistic regression (AUC 0.81), support vector machine (AUC 0.84), and k-nearest neighbors (AUC 0.78), and found that the four most important factors in determining the outcome were preoperative air-bone gap, perforation size, Eustachian tube function, and graft material.

The percentage of graft success in our cohort is similar to the reported anatomical success rate with tympanoplasty, which has ranged from 90% to 99% [3]. The functional hearing success rate in our study was slightly higher, however, at 78% according to the composite definition, compared to that found in a multicentric cohort with a similar postoperative ABG threshold of 40.4% [12]; differences in baseline disease severity, follow-up duration and definitions of hearing success likely explain much of these discrepancies. Likewise, a 10-year long-term follow-up of ECT showed similar graft closure rates and defined functional outcome by ABG threshold of ≤20 dB, which is a broad range and is consistent with the outcome definition utilized in our study [13].

In our study, the higher accuracy of the random forest model compared to the logistic regression model is similar to other studies that have used machine learning for hearing outcome prediction following tympanoplasty; the random forest models had better hearing outcome predictive ability than classical scoring systems like MERI and OOPS, as well as support vector machine (SVM) and k-nearest neighbor (KNN) classifiers, in predicting the postoperative air-bone gap (ABG) [9]. Another AI-based hearing prognosis study conducted after an intact canal wall mastoidectomy with tympanoplasty showed that machine learning models could predict major prognostic factors with a high predictive accuracy with a large cohort of almost 500 patients [11]. The superiority of the random forest models over logistic regression, which assumes linear and additive relationships between the predictor variables and the outcome [9,11] might be due to the fact that the random forest models can capture non-linear interactions between the variables (e.g., the interaction between the size of the perforation and Eustachian tube dysfunction in graft healing).

Our findings are in line with a significant number of studies that have found a correlation between higher baseline hearing levels and larger perforations with worse functional results after tympanoplasty [12,14]. Another multicentric investigation of the predictors of functional outcome after tympanoplasty found that the OOPS score would be correlated with postoperative hearing success, and that worse blood loss during surgery and higher OOPS scores were independent risk factors for hearing failure [12].

In line with previous studies, which linked intraoperatively measured characteristics of the Eustachian tube with the surgical outcomes in CSOM, Eustachian tube dysfunction was demonstrated as the third most important predictor in our model [15]. Persistent ME effusion, negative ME pressure and graft retraction can occur due to poor Eustachian tube function, which can affect the anatomical and functional outcomes [15].

Our findings confirm the comparative studies and meta-analyses that suggest cartilage grafts might provide superior resistance to retraction and re-perforation than the temporalis fascia, especially in high-risk ears [16]. In a similar study, comparing results of type I tympanoplasty done by residents, the use of cartilage grafting and a longer dry period before surgery were determined to be independent predictors of surgical success [17].

The results of this study indicate that machine learning models that use routinely collected pre-operative factors may offer clinically meaningful, personalized risk stratification for patients who undergo tympanoplasty. Such models could be used in the preoperative counselling to establish realistic expectations of hearing improvement, and to help identify patients who would benefit from pre-operative optimisation of Eustachian tube function, a longer dry period before surgery or selection of a cartilage-based approach to the surgery [6,7,17].

Limitations

This study has several limitations. The relatively small sample size of 100 patients from a single center limits the statistical power of the machine learning models and increases the risk of overfitting, despite the use of cross-validation; external validation in larger, multicentric cohorts is necessary before clinical implementation. The retrospective design may have introduced selection and information bias, and the 1-year follow-up period, while adequate for assessing early graft and hearing outcomes, may not capture late graft failures or delayed hearing deterioration. Finally, certain variables that have been implicated in tympanoplasty outcomes in other studies, such as intraoperative blood loss and detailed middle ear mucosal grading, were not consistently available in our records and could not be incorporated into the model [12].

Conclusion

In this retrospective cohort of 100 patients undergoing type I tympanoplasty at ANMC, Gaya, a random forest-based machine learning model demonstrated good discriminative performance (AUC 0.89) for predicting 1-year surgical and audiological outcomes, outperforming logistic regression and other conventional classifiers. Preoperative air-bone gap, perforation size, Eustachian tube function, and graft material were identified as the most important predictors of outcome. With external validation in larger, prospective, multicentric cohorts, such models may serve as useful adjuncts for preoperative risk stratification, patient counselling, and individualized surgical planning in patients undergoing tympanoplasty.

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