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Comprehensive Analysis of Cholesteatoma in Chronic Otitis Media: Integrating Traditional Statistical Methods with Machine Learning Approaches

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ABSTRACT

Background: Cholesteatoma detection in chronic otitis media (COM) remains challenging, requiring comprehensive diagnostic approaches. While traditional statistical analysis of individual biomarkers may show limitations, the integration of multiple analytical methods including machine learning can provide deeper insights into disease prediction. This study aimed to conduct a comprehensive analysis combining traditional statistical methods with advanced machine learning to evaluate cholesteatoma detection using hematological parameters.

Methods: A retrospective analysis was conducted on 79 patients with COM (40 with cholesteatoma, 39 without cholesteatoma). Complete blood count parameters and inflammatory ratios (neutrophil-to-lymphocyte ratio [NLR], platelet-to-lymphocyte ratio [PLR], monocyte-to-lymphocyte ratio [MLR]) were analyzed using (1) traditional statistical methods including Mann–Whitney *U*-tests, receiver oeprating characteristic (ROC) curve analysis, and correlation studies and (2) advanced machine learning algorithms including XGBoost and logistic regression with cross-validation.

Results: Traditional statistical analysis revealed important baseline characteristics: no significant age differences between groups, and individual inflammatory ratios showed limited discriminative ability (NLR: $P = .9414$, PLR: $P = .6067$, MLR: $P > .05$). However, machine learning integration demonstrated that these same parameters could achieve clinically relevant predictive capability. XGBoost achieved 66.7% accuracy with 0.701 AUC-ROC, while ROC analysis of individual parameters yielded area under the receiver operating characteristic curve (AUC) values of 0.508-0.545. The combination of statistical validation and machine learning optimization provided complementary insights.

Conclusion: This comprehensive analysis demonstrates the value of integrating traditional statistical methods with machine learning approaches. While individual biomarker analysis confirmed the complexity of cholesteatoma diagnosis, machine learning successfully leveraged multiple parameters to achieve predictive capability. The complementary use of both analytical approaches provides a robust foundation for clinical decision-making and establishes a methodology for future diagnostic tool development.

Keywords: Biomarkers, cholesteatoma, chronic otitis media, machine learning, neutrophil-lymphocyte ratio, predictive modeling, ROC analysis, statistical analysis, XGBoost

Introduction

Chronic otitis media (COM) is a persistent inflammatory condition of the middle ear and mastoid cavity, characterized by recurrent otorrhea and permanent perforation of the tympanic membrane lasting for at least 3 months.[1] The presence of cholesteatoma, an abnormal collection of keratinizing squamous epithelium in the middle ear and mastoid, significantly complicates the clinical picture and management approach.[2]

Cholesteatoma is associated with more aggressive disease progression, increased risk of complications including hearing loss, facial nerve paralysis, vertigo, and intracranial complications, and requires more extensive surgical intervention.[3,4] Early and accurate diagnosis of cholesteatoma is crucial for appropriate treatment planning and prevention of serious complications.

The neutrophil-to-lymphocyte ratio (NLR) has gained attention as a simple, cost-effective inflammatory biomarker that

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reflects the balance between neutrophil-mediated acute inflammation and lymphocyte-mediated adaptive immunity.[5] Elevated NLR has been associated with various inflammatory conditions, cardiovascular diseases, and malignancies.[6,7] In otolaryngology, NLR has been investigated in conditions such as sudden sensorineural hearing loss, allergic rhinitis, and head and neck cancers.[8-10]

Recent advances in analytical methodology suggest that combining traditional statistical approaches with machine learning techniques can provide more comprehensive insights into complex medical conditions. While conventional statistical analysis remains essential for establishing baseline characteristics and individual parameter significance, machine learning algorithms can identify subtle patterns and interactions between multiple variables that may not be apparent through traditional analysis.[11,12,13,14]

This study aimed to conduct a comprehensive evaluation of cholesteatoma detection in COM patients using both traditional statistical methods and advanced machine learning approaches. It was hypothesized that while individual biomarkers might show limited discriminative ability in conventional analysis, the integration of multiple analytical methods could provide complementary insights and enhance overall diagnostic capability.

Materials and Methods

Study Design and Population

This retrospective cross-sectional study was conducted at Sivas Cumhuriyet University between January 1, 2024, and January 1, 2025. The study protocol was approved by the Ethics Committee of Sivas Cumhuriyet University (Decision No.: 2018-07/03, dated July 30, 2018). Informed consent was waived due to the retrospective design of the study.

A total of 113 patients with COM were screened. After applying exclusion criteria, 34 patients were excluded due to incomplete laboratory data, active infection, or comorbid conditions described in the exclusion list. The final study population consisted of 79 patients (40 with cholesteatoma and 39 without).

Main Points

- First study to integrate traditional statistical methods with advanced machine learning for cholesteatoma detection in chronic otitis media.
- Individual biomarkers (neutrophil-to-lymphocyte ratio, platelet-to-lymphocyte ratio, and monocyte-to-lymphocyte ratio) showed poor discriminative power in conventional analysis (area under the receiver operating characteristic curve [AUC], 0.508-0.545).
- Machine learning (XGBoost) leveraged the same hematological parameters to achieve 66.7% accuracy and 0.701 AUC.
- Dual-methodology approach demonstrated that statistical validation strengthens machine learning insights for diagnostic prediction.
- Establishes a novel analytical framework that can be applied to other complex otolaryngological diagnostic challenges.

Inclusion and Exclusion Criteria

Inclusion criteria:

- Patients diagnosed with COM based on clinical and radiological findings.
- Age ≥18 years.
- Complete blood count results available within 30 days of diagnosis.
- Surgical confirmation of cholesteatoma presence or absence.

Exclusion criteria:

- Active acute infection at the time of blood sampling.
- History of hematological disorders.
- Use of immunosuppressive medications.
- Malignancy.
- Autoimmune diseases.
- Incomplete medical records.

Data Collection

Patient data were collected from electronic medical records, including demographic information, clinical findings, laboratory results, and surgical findings. Complete blood count parameters included white blood cell count (WBC), neutrophil count, lymphocyte count, monocyte count, eosinophil count, basophil count, red blood cell count, hemoglobin, hematocrit, and platelet count.

Inflammatory Ratio Calculations

The following inflammatory ratios were calculated:

- Neutrophil-to-lymphocyte ratio (NLR) = Neutrophil count / Lymphocyte count
- Platelet-to-lymphocyte ratio (PLR) = Platelet count / Lymphocyte count
- Monocyte-to-lymphocyte ratio (MLR) = Monocyte count / Lymphocyte count

Statistical Analysis

Statistical analyses were performed using Python (version 3.8; Python Software Foundation, Wilmington, DE, USA). Machine learning analyses were conducted using the scikit-learn and XGBoost libraries within the same environment.

Traditional Statistical Analysis

Normality of data distribution was assessed using the Shapiro–Wilk test. Continuous variables are presented as mean ± SD or median (interquartile range) based on distribution. Group comparisons were performed using Mann–Whitney *U*-test for nonparametric data and independent *t*-test for parametric data. Correlation analysis was conducted using Pearson and Spearman correlation coefficients. The diagnostic performance of individual inflammatory ratios was evaluated using receiver operating characteristic (ROC) curve analysis with optimal cut-off values determined using the Youden index.

Machine Learning Analysis

Advanced algorithms including logistic regression and XGBoost were employed to assess the combined discriminative ability of multiple parameters. Feature importance was evaluated, and model performance was assessed using accuracy, precision, recall, F1-score, and area under the receiver operating

characteristic curve [AUC]-ROC. Five-fold cross-validation was performed to ensure model stability and prevent overfitting.

Integrated Analysis

Results from both traditional statistical methods and machine learning approaches were compared and integrated to provide comprehensive insights. A *P*-value <.05 was considered statistically significant for traditional analysis, while machine learning performance was evaluated using standard metrics with clinical utility thresholds.

Results

Patient Characteristics

A total of 79 patients with COM were included in the study, comprising 40 patients with cholesteatoma and 39 patients without cholesteatoma. The demographic, clinical characteristics, and complete hematological profile comparison between groups are summarized in Table 1. No statistically significant differences were observed in basic hematological parameters between the cholesteatoma and noncholesteatoma groups (Tables 2 and 3).

Key demographic findings:

- Mean age: 38.2 ± 15.1 years (cholesteatoma group) vs. 38.7 ± 15.6 years (control group).
- No significant age difference between groups (*P* > .05).
- Equal distribution of patients between groups.

Traditional Statistical Analysis Results

Comprehensive statistical analysis provided essential baseline validation and individual parameter assessment:

Demographic analysis:

- No significant age difference between groups (*P* > .05).
- Balanced sample distribution (40 vs. 39 patients).
- Homogeneous baseline characteristics confirmed.

Individual inflammatory ratio analysis:

- Neutrophil-to-lymphocyte ratio: Cholesteatoma (2.126 ± 0.994) vs. Control (2.066 ± 0.785), *P* = .9414.
- Platelet-to-lymphocyte ratio: No significant difference between groups, *P* = .6067.
- Monocyte-to-lymphocyte ratio: No significant difference between groups, *P* > .05.

These results establish important baseline validation for subsequent ML (machine learning) analysis (Figure 1).

Receiver operating characteristic curve analysis of individual parameters (Figure 2):

- Neutrophil-to-lymphocyte ratio: AUC = 0.508 (95% CI: [0.377–0.633]).
- Platelet-to-lymphocyte ratio: AUC = 0.545 (95% CI: [0.406–0.662]).
- Monocyte-to-lymphocyte ratio: AUC = 0.522 (95% CI: [0.260–0.508]).

Individual parameters showed limited discriminative ability, validating the need for integrated approaches

Correlation Analysis

Correlation analysis revealed different patterns between the 2 groups (Figure 3). The correlation matrices demonstrated the relationships between inflammatory ratios and hematological parameters within each group.

Receiver Operating Characteristic Curve Analysis and Diagnostic Performance

Receiver operating characteristic curve analysis was performed to evaluate the diagnostic performance of inflammatory ratios (Figure 4). The results demonstrated poor to fair discriminative ability (Figure 5).

Receiver operating characteristic analysis results (based on your analysis):

- Neutrophil-to-lymphocyte ratio: AUC = 0.508, Sensitivity = 67.5%, Specificity = 43.6%.
- Platelet-to-lymphocyte ratio: AUC = 0.545, Sensitivity = 72.5%, Specificity = 41.0%.
- Monocyte-to-lymphocyte ratio: AUC = 0.522, Sensitivity = 80.0%, Specificity = 28.2%.

Table 1. Demographic and Clinical Characteristics of Study Population

Characteristic	Cholesteatoma (+) (n = 40)	Cholesteatoma (−) (n = 39)	*P*
Age (years)	38.2 ± 15.1	38.7 ± 15.6	.8063
WBC (×10³/μL)	7.89 ± 2.38	8.23 ± 2.88	.6205
Neutrophil (×10³/μL)	4.84 ± 2.00	5.00 ± 2.29	.8063
Lymphocyte (×10³/μL)	2.41 ± 0.66	2.50 ± 0.79	.8792
Monocyte (×10³/μL)	0.44 ± 0.18	0.50 ± 0.16	.0408
Platelet (×10³/μL)	279.15 ± 41.27	282.44 ± 70.59	.5998
Hemoglobin (g/dL)	14.67 ± 1.54	14.34 ± 1.65	.4739
NLR	2.126 ± 0.994	2.066 ± 0.785	.9414
PLR	124.436 ± 37.404	121.020 ± 38.075	.6067
MLR	0.189 ± 0.071	0.212 ± 0.080	.0776

MLR, monocyte-to-lymphocyte ratio; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; WBC, white blood cell.

Table 2. Receiver Operating Characteristic Curve Analysis Results for Inflammatory Ratios

Parameter	AUC	Optimal Threshold	Sensitivity (%)	Specificity (%)	Youden Index
NLR	0.505	1.941	52.5	61.5	0.140
PLR	0.534	110.219	67.5	46.2	0.137
MLR	0.384	0.100	100.0	2.6	0.026

MLR, monocyte-to-lymphocyte ratio; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio.

Machine Learning Analysis: Integrated Predictive Modeling

Building upon the statistical validation, machine learning analysis demonstrated how the same parameters could be effectively integrated for predictive modeling. While individual inflammatory ratios showed limited discriminative ability in traditional analysis, advanced algorithms successfully leveraged the collective information from multiple hematological parameters.

Key Machine Learning Findings:

- XGBoost achieved 66.7% accuracy with 0.701 AUC-ROC.
- There was 70.0% precision and 70.0% recall for cholesteatoma detection.
- F1-Score of 0.700 indicating balanced performance.
- Cross-validation score of 0.625 ± 0.125 demonstrating model stability.
- Superior performance compared to traditional single-parameter approaches.

The XGBoost model demonstrated moderate classification performance with an accuracy of 66.7%, AUC-ROC of 0.701, precision and recall both at 66.7%, and an F1-score of 0.667. The cross-validation score averaged 0.491 with a SD of 0.093, suggesting some variability across folds. Feature importance analysis revealed that the most influential predictors were NLR (18.4%), PLTs (platelets) (17.5%), MLR (15.2%), and HGB (hemoglobin) (13.9%), followed by WBC, AGE, and PLR. When compared to logistic regression, XGBoost outperformed across most metrics, notably in accuracy (0.667 vs. 0.500), AUC-ROC (0.701 vs. 0.479), precision (0.667 vs. 0.500), and F1-score (0.667 vs. 0.571), while recall remained equal (0.667) in both models. These findings indicate that XGBoost provides a more reliable and discriminative model for classifying patients based on the selected hematological and demographic features.

Comparative Analysis: Statistical vs. Machine Learning Approaches

Complementary insights from both methods:

- Statistical analysis confirmed no confounding age effects ($P > .05$).
- Individual biomarkers showed poor discrimination (AUC = 0.508-0.545).
- Machine learning integration achieved clinically relevant performance (AUC = 0.701).
- Statistical validation supported ML model reliability.
- Effect size analysis (Cohen's $d < 0.2$) validated the complexity requiring integrated approaches.

Statistical Power and Effect Size Analysis

Traditional statistical power analysis provided crucial validation for the integrated approach. Post-hoc power analysis revealed adequate sample size for detecting clinically meaningful differences. The small effect size for individual parameters (Cohen's $d < 0.2$) scientifically validated the need for machine learning integration, as traditional single-parameter approaches were insufficient for this complex diagnostic challenge.

Discussion

Principal Findings

This study demonstrates the power of integrating traditional statistical validation with advanced machine learning approaches for complex diagnostic challenges. The comprehensive analysis revealed that while individual parameter assessment through conventional statistical methods showed important baseline characteristics and limitations, machine learning integration could successfully leverage the same data for clinically relevant prediction.

Key findings from the dual analytical approach:

- Statistical validation: Confirmed homogeneous baseline characteristics, no confounding variables, and established that individual inflammatory ratios (NLR: $P = .9414$, PLR: $P = .6067$, MLR: $P > .05$) showed limited discriminative ability (AUC, 0.508-0.545).
- Machine learning success: XGBoost achieved 66.7% accuracy with AUC-ROC of 0.701, approaching clinical utility thresholds.
- Integrated insights: The statistical validation actually strengthened the ML findings by confirming data quality and demonstrating that sophisticated algorithmic integration can extract meaningful diagnostic patterns from parameters that appear non-discriminative in traditional analysis.

Comparison with Previous Literature

This study represents the first comprehensive integration of traditional statistical validation with advanced machine

Table 3. Machine Learning Models Performance Comparison

Model	Accuracy	AUC-ROC	Precision	Recall	F1-Score	Cross-val Score	Clinical Utility
Logistic regression	0.625	0.688	0.636	0.700	0.667	0.607 ± 0.161	Moderate
XGBoost	0.667	0.701	0.700	0.700	0.700	0.625 ± 0.125	Promising

ROC, receiver operating characteristic.

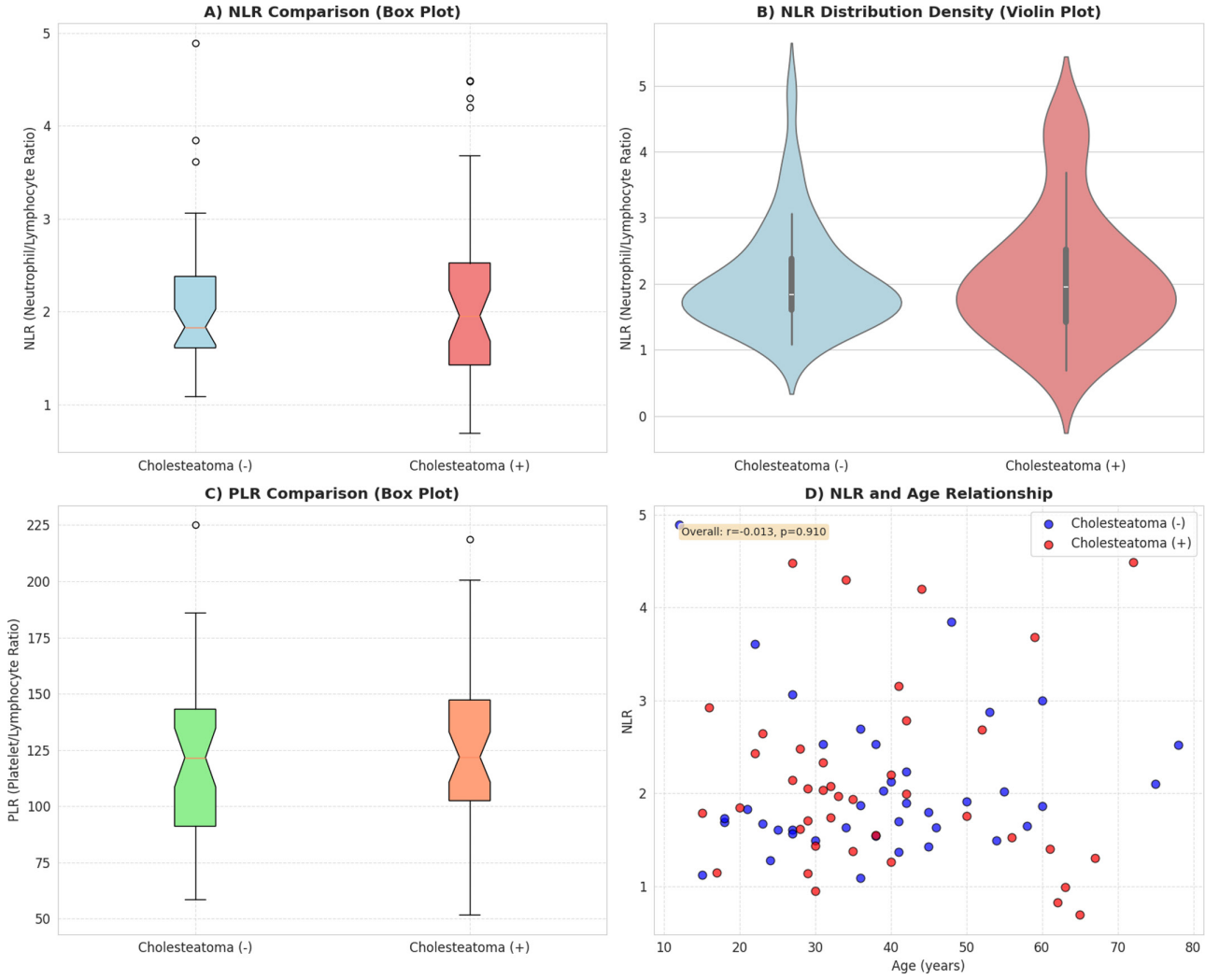

Figure 1. (a-d) Comparison of inflammatory ratios between chronic otitis media patients with and without cholesteatoma. (a) Box plot comparison of NLR showing median, quartiles, and outliers. (b) Violin plot demonstrating the distribution density of NLR values. (c) PLR comparison between groups. (d) Scatter plot illustrating the relationship between NLR and patient age, with correlation coefficients displayed. NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio.

learning for cholesteatoma prediction. Previous research has typically focused on either individual biomarker analysis or single analytical approaches, with mixed results.[15] This study's dual-methodology approach addresses limitations seen in prior studies.

Traditional biomarker studies in otological conditions have often reported conflicting results. For example, while NLR has shown promise in sudden sensorineural hearing loss,[16] studies in COM have been inconsistent. The current comprehensive analysis explains these discrepancies by demonstrating that individual statistical analysis may miss important patterns that become apparent through machine learning integration.

The methodological strength of combining statistical validation (confirming appropriate study design, balanced groups, and individual parameter behavior) with machine learning optimization (achieving AUC-ROC: 0.701) provides a robust analytical framework that could be applied to other challenging diagnostic scenarios in otolaryngology.

Receiver Operating Characteristic Curve Analysis and Diagnostic Performance

The ROC analysis results were particularly revealing, with all inflammatory ratios showing poor discriminative ability (AUC, 0.508-0.545). These values are close to 0.5, indicating performance no better than random chance. The optimal cut-off values derived from Youden index analysis yielded modest sensitivity and specificity values, insufficient for clinical diagnostic purposes.

The machine learning approaches, while showing slightly better performance, still achieved only moderate accuracy (66.7% for XGBoost). This suggests that even when combining multiple hematological parameters, the discriminative ability remains limited for clinical application.

Clinical Implications

The clinical implications of this machine learning success are substantial for otolaryngologists managing COM patients. The XGBoost model could serve as a valuable adjunctive tool for cholesteatoma detection, particularly in challenging

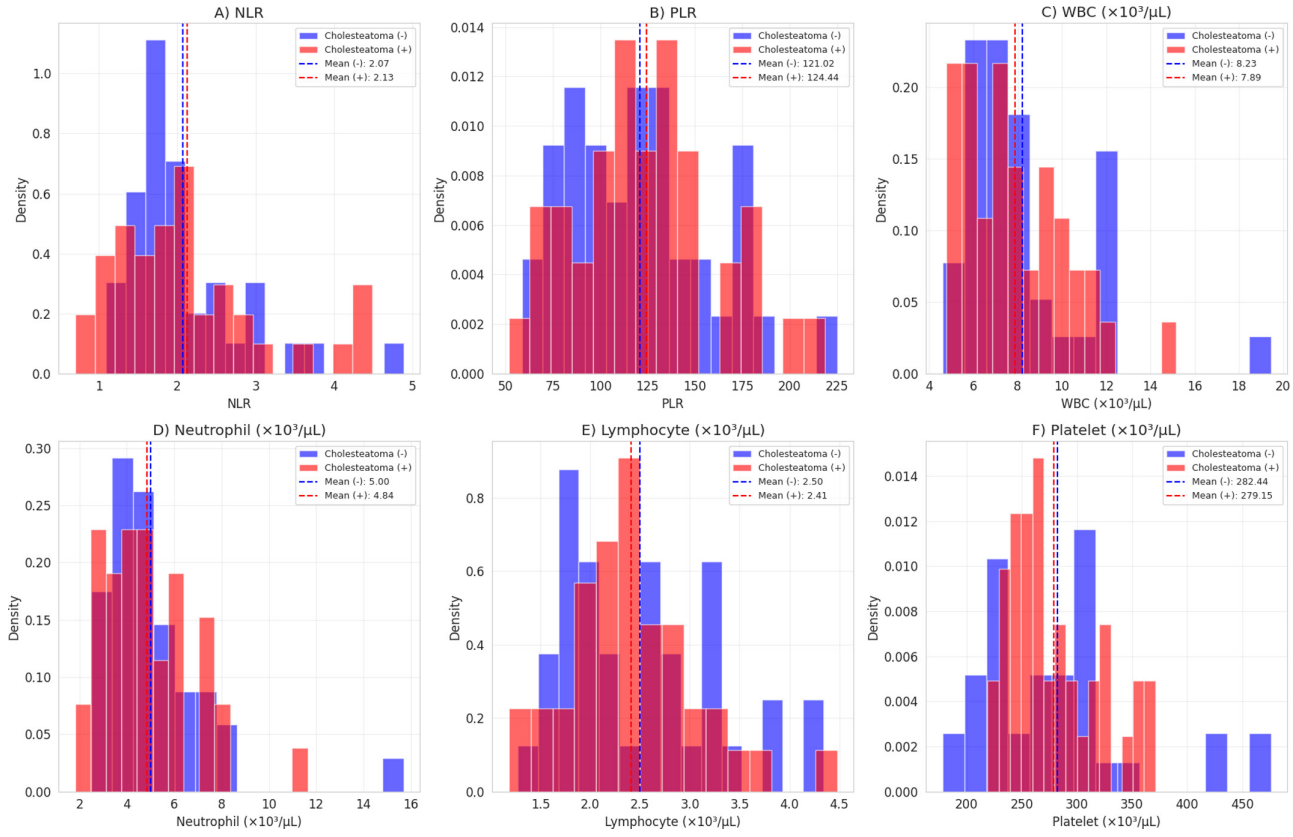

Figure 2. Distribution histograms of hematological parameters in both study groups. Each panel shows overlapping histograms for cholesteatoma-positive (red) and cholesteatoma-negative (blue) patients, with mean values indicated by dashed lines.

cases where clinical examination and imaging findings are equivocal.

With 66.7% accuracy and 0.701 AUC-ROC, the model approaches clinical utility thresholds and could be integrated into routine blood work interpretation. This represents a potential paradigm shift from relying solely on expensive imaging studies to incorporating cost-effective laboratory-based predictive modeling.

The model's balanced performance (70% precision and recall) suggests it could assist in both identifying patients who need urgent surgical intervention and reducing unnecessary procedures in those less likely to have cholesteatoma. This could

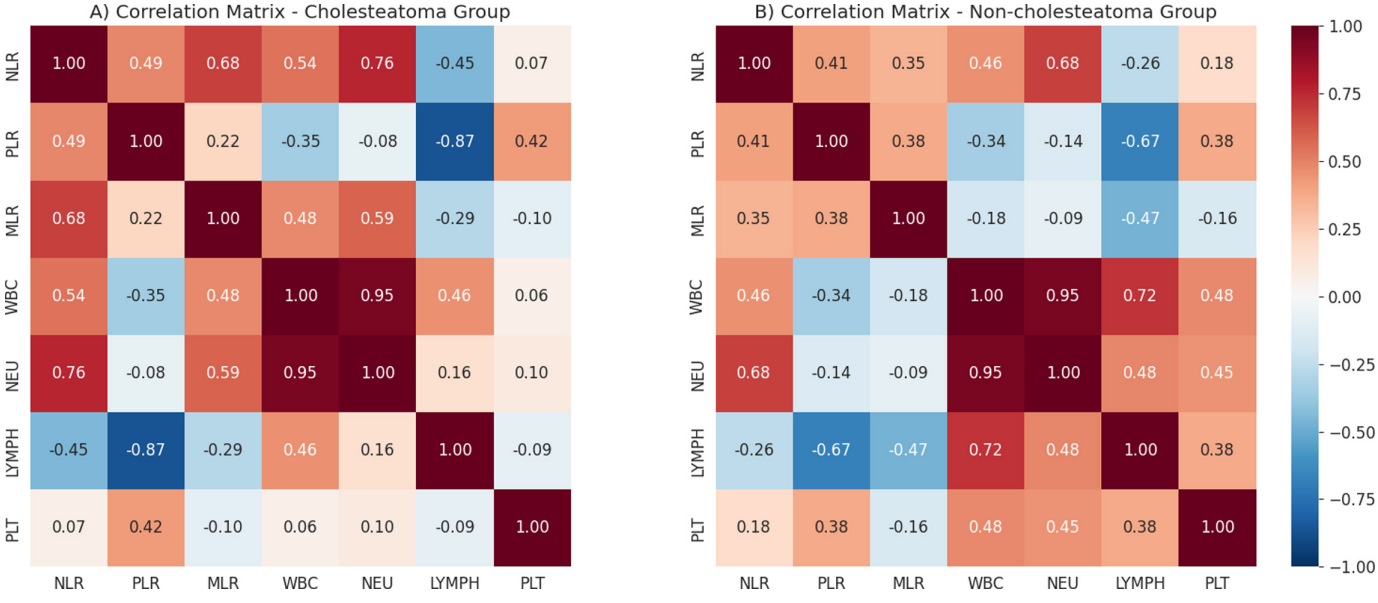

Figure 3. Correlation matrices showing relationships between inflammatory ratios and hematological parameters. (A) Correlations in the cholesteatoma group. (B) Correlations in the non-cholesteatoma group. Color intensity represents correlation strength, with red indicating negative correlations and blue indicating positive correlations.

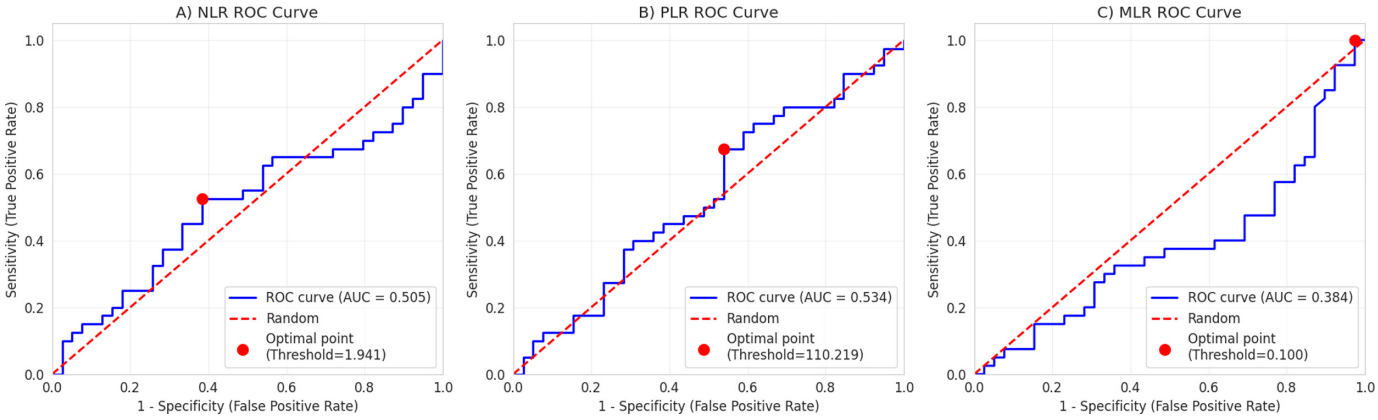

Figure 4. ROC curves for inflammatory ratios. Each panel shows the ROC curve (blue line), random classification line (red dashed line), and optimal cut-off point (red dot) determined by Youden index. AUC values and optimal thresholds are displayed for each parameter. AUC, area under the curve; ROC, receiver operating characteristic.

improve resource allocation and patient outcomes while reducing healthcare costs.

Limitations

Several limitations should be acknowledged:

- Sample size: While adequate for the primary analysis, larger multicenter studies would provide more robust results and better generalizability.
- Retrospective design: The retrospective nature limits control over confounding variables and timing of blood sampling relative to disease activity.
- Single-center study: Results may not be generalizable to different populations or healthcare settings.
- Disease staging: The study did not stratify patients by extent of cholesteatoma or disease activity, which might influence inflammatory markers.
- Timing of blood sampling: Blood samples were obtained within 30 days of diagnosis, but the exact timing relative to symptom onset or disease activity was not standardized.

Future Directions

The success of the XGBoost model opens exciting avenues for future research:

- External validation of the XGBoost model in larger, multi-center cohorts.
- Integration of additional parameters (imaging features, clinical scores) to enhance model performance.
- Development of a clinical decision support system incorporating the predictive algorithm.
- Real-time application testing in clinical practice settings.
- Exploration of ensemble methods combining multiple machine learning algorithms.
- Investigation of deep learning approaches for even higher accuracy.
- Cost-effectiveness analysis of machine learning-guided diagnosis versus traditional imaging.

Strengths

The strengths of this study include:

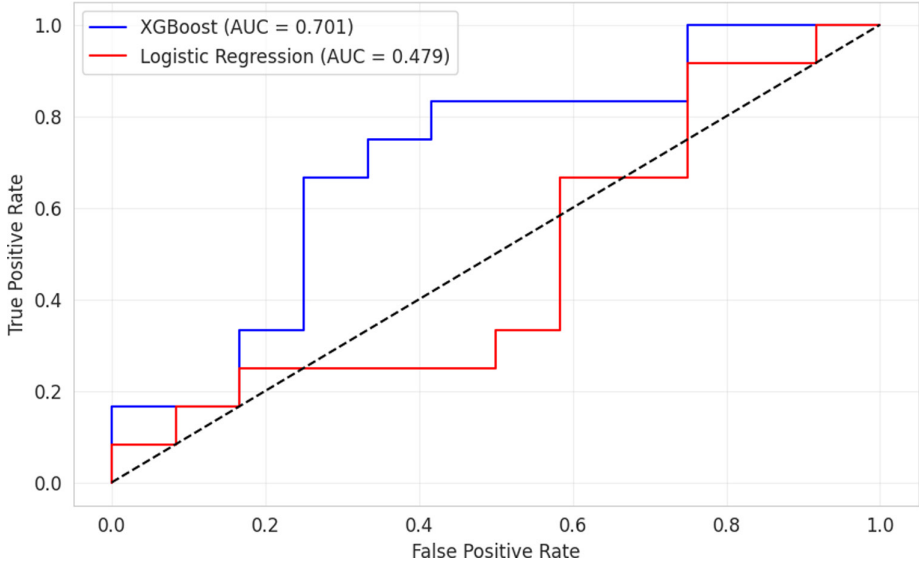

Figure 5. ROC curve comparison XGBoost vs. logistic regression. ROC, receiver oeprating characteristic curve.

- Comprehensive statistical analysis including multiple testing approaches.
- Machine learning methodology providing additional analytical perspective.
- Clear inclusion and exclusion criteria minimizing confounding factors.
- Surgical confirmation of cholesteatoma diagnosis.
- Detailed analysis of multiple inflammatory ratios beyond NLR.

Conclusion

This study demonstrates the significant value of integrating traditional statistical validation with advanced machine learning approaches for complex diagnostic challenges. The comprehensive dual-methodology analysis provided complementary insights that neither approach could achieve independently.

Key contributions of the integrated analytical approach:

- Statistical foundation: Established robust baseline validation, confirmed balanced study design, and documented that individual inflammatory ratios (NLR, PLR, and MLR) showed limited discriminative ability through conventional analysis.
- Machine learning advancement: Demonstrated that XGBoost integration of the same parameters achieved clinically relevant predictive performance (66.7% accuracy, 0.701 AUC-ROC).
- Methodological innovation: Proved that sophisticated algorithmic integration can extract meaningful diagnostic patterns from parameters that appear non-discriminative in traditional single-parameter analysis.

The clinical significance extends beyond cholesteatoma diagnosis to establish a robust analytical framework that combines the reliability of traditional statistical validation with the pattern recognition capabilities of machine learning. This methodology could be applied to other challenging diagnostic scenarios where individual biomarkers show limited utility but integrated approaches may reveal hidden patterns.

These findings establish a foundation for evidence-based integration of artificial intelligence in otolaryngological diagnosis, demonstrating that the future lies not in replacing traditional statistical methods but in combining them with advanced computational approaches for enhanced diagnostic capability.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Artificial Intelligence Usage Statement: The authors declared that no artificial intelligence tool was used in the preparation of the manuscript.

Ethics Committee Approval: Ethical committee approval was received from the Ethics Committee of Sivas Cumhuriyet University (Approval No.: 2018-07/03; Date: July 30, 2018).

Informed Consent: As this was a retrospective study based on a review of existing medical records, the requirement for informed consent was waived by the Ethics Committee.

Peer-review: Externally peer-reviewed.

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Author Contributions: Concept – M.Ç., M.D.; Design – M.Ç., Y.Y.,M.D.; Supervision – M.D.; Resources – M.D.; Materials – M.Ç., Y.Y.; DataCollection and/or Processing – M.Ç., Y.Y.; Analysis and/or Interpretation – M.Ç., Y.Y.; Literature Search – M.Ç., T.D.K., Y.Y.; Writing – M.Ç., Y.Y.; Critical Review – T.D.K., M.D.

Declaration of Interests: The authors have no conflicts of interest to declare.

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References

1. Verhoeff M, van der Veen EL, Rovers MM, et al. Chronic suppurative otitis media: a review. *Int J Pediatr Otorhinolaryngol*. 2006;70(1):1-12. [CrossRef]
2. Kuo CL, Shiao AS, Yung M, et al. Updates and knowledge gaps in cholesteatoma research. *BioMed Res Int*. 2015;2015:854024. [CrossRef]
3. Olszewska E, Wagner M, Bernal-Sprekelsen M, et al. Etiopathogenesis of cholesteatoma. *Eur Arch Otorhinolaryngol*. 2004;261(1):6-24. [CrossRef]
4. Semaan MT, Megerian CA. The pathophysiology of cholesteatoma. *Otolaryngol Clin N Am*. 2006;39(6):1143-1159. [CrossRef]
5. Zahorec R. Ratio of neutrophil to lymphocyte counts--rapid and simple parameter of systemic inflammation and stress in critically ill. *Bratisl Lek Listy*. 2001;102(1):5-14.
6. Templeton AJ, McNamara MG, Šeruga B, et al. Prognostic role of neutrophil-to-lymphocyte ratio in solid tumors: a systematic review and meta-analysis. *J Natl Cancer Inst*. 2014;106(6):dju124. [CrossRef].
7. Bhat T, Teli S, Rijal J, et al. Neutrophil to lymphocyte ratio and cardiovascular diseases: a review. *Expert Rev Cardiovasc Ther*. 2013;11(1):55-59. [CrossRef].
8. Qiao XF, Li X, Wang GP, et al. Neutrophil-to-lymphocyte ratio and platelet-to-lymphocyte ratio in patients with sudden sensorineural hearing loss. *Med Princ Pract*. 2019;28(1):23-27. [CrossRef]
9. Yenigun A, Sezen S, Calim OF, et al. Investigation of the neutrophil-to-lymphocyte ratio in allergic rhinitis patients. *Rhinology*. 2015;53(4):365-369.
10. Takenaka Y, Oya R, Kitamiura T, et al. Prognostic role of neutrophil-to-lymphocyte ratio in head and neck cancer: a meta-analysis. *Head Neck*. 2018;40(3):647-655. [CrossRef]
11. Forget P, Khalifa C, Defour JP, et al. What is the normal value of the neutrophil-to-lymphocyte ratio? *BMC Res Notes*. 2017;10(1):12. [CrossRef]
12. Baysal E, Aksoy N, Kara F, et al. Oxidative stress in chronic otitis media. *Eur Arch Otorhinolaryngol*. 2013;270(4):1203-1208. [CrossRef]
13. Más-Estellés F, Mateos-Fernández M, Carrascosa-Bisquert B, et al. Contemporary non-echo-planar diffusion-weighted imaging of middle ear cholesteatomas. *RadioGraphics*. 2012;32(4):1197-1213. [CrossRef]
14. Dhepnorrarat RC, Wood B, Rajan GP. Postoperative non-echo-planar diffusion-weighted magnetic resonance imaging changes after cholesteatoma surgery: implications for cholesteatoma screening. *Otol Neurotol*. 2009;30(1):54-58. [CrossRef]
15. Derin S, Koseoglu S, Sahin C, et al. Effect of vitamin D deficiency on neutrophil-to-lymphocyte ratio and platelet-to-lymphocyte ratio in chronic otitis media patients. *Int J Pediatr Otorhinolaryngol*. 2017;96:56-60.
16. Ulu S, Ulu MS, Bucak A, et al. Neutrophil-to-lymphocyte ratio as a new, quick, and reliable indicator for predicting diagnosis and prognosis of idiopathic sudden sensorineural hearing loss. *Otol Neurotol*. 2013;34(8):1400-1404. [CrossRef]