



Received: 19 Aug 2026
Revised: 29 Aug 2026
Accepted: 13 Sep 2026
Published: 30 Sep 2026

Volume 12 Issue 09, 2026
Page No - 308-311
DOI - 10.55640/ijmsdh-12-09-36

Article Citation:

Copyright: © 2026 The Authors. Published by IJMSDH under the Creative Commons CC BY License

Artificial Intelligence-Based Prediction Of Recurrence After Endoscopic Dacryocystorhinostomy: A Narrative Review

Tursunov D.K.¹, Kosimov K.K.²
Andijan State Medical Institute, Uzbekistan

Abstract

Postoperative recurrence remains a clinically significant limitation of endoscopic dacryocystorhinostomy (EDCR). This narrative review synthesizes current evidence on artificial intelligence (AI) and machine learning (ML) applications for surgical outcome prediction in ophthalmology and otolaryngology, and outlines a methodological framework — combining preoperative CT-based anatomical features with clinical variables — for the future development of an interpretable, externally validated AI-based recurrence-prediction model for EDCR.

Keywords: Endoscopic dacryocystorhinostomy, recurrence, artificial intelligence, machine learning, predictive model, nasolacrimal duct obstruction.

Introduction

Endoscopic dacryocystorhinostomy (EDCR) has become the preferred surgical approach for nasolacrimal duct obstruction owing to its minimally invasive nature, absence of external scarring, and favorable recovery profile [5, 18]. Despite reported success rates ranging from 84% to 95% [5], a clinically significant proportion of patients experience postoperative recurrence, most commonly related to ostial stenosis, granulation tissue overgrowth, synechiae formation, and individual anatomical variability of the nasal cavity. Predicting which patients are at elevated risk of recurrence prior to surgery remains a substantial clinical challenge, as conventional statistical models often fail to capture the complex, non-linear interactions among demographic, anatomical, and intraoperative variables.

Artificial intelligence (AI) and, more specifically, machine learning (ML) have emerged as promising tools for surgical outcome prediction across multiple specialties, offering the ability to integrate heterogeneous data sources — clinical, radiological, and intraoperative — into unified predictive frameworks [17, 18]. Within otolaryngology and ophthalmology, AI-based approaches have already demonstrated utility in



diagnostic image interpretation, prognostic stratification, and surgical planning [3, 8, 10].

The purpose of this narrative review is to synthesize the current evidence on the application of AI and machine learning for predicting surgical outcomes and recurrence in lacrimal and otorhinolaryngological surgery, with particular attention to methodological approaches that could be extrapolated to recurrence prediction after endoscopic dacryocystorhinostomy, and to outline directions for future research and clinical implementation.

1. MACHINE LEARNING FUNDAMENTALS RELEVANT TO SURGICAL OUTCOME PREDICTION

Machine learning refers to a family of computational algorithms capable of identifying patterns within data without being explicitly programmed for a specific rule set [17]. In contrast to traditional regression-based statistical models, ML algorithms — including random forests, gradient boosting, support vector machines, and deep neural networks — can model complex, non-linear relationships among a large number of variables simultaneously [11]. In surgical practice, this capability has translated into models capable of predicting postoperative complications, length of stay, and long-term functional outcomes with accuracy that frequently exceeds conventional risk scores [11].

A recent update on the application of machine learning in surgery highlighted that, despite strong performance across diverse surgical specialties, several methodological limitations persist, including opaque "black box" outputs, degraded performance upon external validation, and difficulty modeling rare events such as low-incidence recurrence [11]. These limitations are directly relevant to lacrimal surgery, where recurrence, although clinically important, remains a comparatively infrequent event that complicates model training on single-center datasets.

Habehh and Gohel emphasized that successful clinical translation of machine learning tools in healthcare requires not only high predictive accuracy but also interpretability and robust external validation across heterogeneous patient populations [9]. Sarker similarly noted that the choice of algorithm should be guided by the nature of the available data, distinguishing between supervised approaches suited to labeled outcome data — such as recurrence versus non-recurrence — and unsupervised approaches more appropriate for exploratory pattern discovery [17].

2. AI-BASED OUTCOME PREDICTION IN OPHTHALMIC AND HEAD-AND-NECK SURGERY

Within ophthalmology, AI-based surgical outcome prediction has been most extensively investigated in the context of glaucoma surgery. A systematic review by Kailani and colleagues evaluated the current evidence on AI applications for predicting postoperative outcomes in glaucoma surgery, concluding that AI-based models, particularly those integrating structured clinical variables with imaging-derived features, demonstrated superior predictive performance compared with traditional statistical approaches, although external validation across independent cohorts remained limited [10]. This methodological trajectory closely parallels the informational challenge encountered in EDCR outcome prediction, where structured clinical data (age, sex, laterality, prior surgery) could similarly be combined with imaging-derived anatomical features (ostium size, agger nasi pneumatization, septal deviation) to construct a comparably structured predictive model.

AI applications in refractive surgery have similarly demonstrated that models trained on structured tabular data, imaging, and multimodal inputs outperform traditional nomogram-based approaches in predicting surgical outcomes and refining patient selection [19]. This convergence of imaging and clinical data streams represents a methodological template directly transferable to lacrimal surgery, where preoperative computed tomography-dacryocystography already provides a rich source of quantifiable anatomical features.

Beyond ophthalmology, radiomic and machine-learning-based evaluation of pretreatment imaging has been applied to prognosis prediction in head and neck oncology. Nakajo and colleagues demonstrated that machine-learning-based analysis of pretreatment 18F-FDG-PET/CT radiomic features improved prognostic stratification in patients with laryngeal cancer compared with conventional clinical staging alone [15], illustrating the broader principle that quantitative imaging biomarkers, when combined with machine learning, can meaningfully augment prognostic accuracy in head and neck pathology — a principle directly applicable to CT-based prediction of EDCR recurrence.

3. AI ADOPTION AND CLINICAL TRANSLATION IN OTOLARYNGOLOGY

Several narrative and systematic reviews have examined the broader landscape of AI adoption in otolaryngology-head and neck surgery. Bur and colleagues provided one of the earliest state-of-the-art reviews summarizing applications across diagnosis, prognosis, and surgical decision-making [5], while Tama and colleagues subsequently catalogued recent advances spanning audiology, rhinology, and head and neck oncology [18]. More recently, Alter and colleagues offered an introductory narrative review specifically addressing machine learning and generative AI for practicing otolaryngologists, underscoring both



the expanding scope of clinical applications and the persistent gap between theoretical potential and routine clinical implementation [3].

Clinical adoption remains an important consideration. A mixed-methods survey by Asokan and colleagues found that, while otolaryngologists and rhinologists generally view AI favorably as a diagnostic and predictive aid, concerns persist regarding transparency, workflow integration, and medico-legal accountability [4]. These concerns are directly relevant to any future AI-based recurrence prediction tool for EDCR, which would need to be interpretable and clinically actionable rather than a purely statistical black box.

Predictive applications extend beyond prognosis alone. Esce and colleagues demonstrated that an AI-based model could accurately predict nodal metastasis in oral tongue squamous cell carcinoma from clinical and imaging variables [8], while Alabi and colleagues developed an interpretable machine learning system for risk stratification in oropharyngeal cancer [1] — both illustrating that interpretable, clinically integrated prediction models are achievable even in complex head and neck pathology, supporting the feasibility of a similarly structured model for EDCR recurrence.

4. TOWARD AN AI-BASED RECURRENCE-PREDICTION FRAMEWORK FOR EDCR

Translating these methodological advances into a recurrence-prediction algorithm for EDCR would require several sequential steps. First, a structured multicenter dataset combining preoperative CT-based anatomical measurements, demographic and clinical variables, and standardized postoperative outcome definitions would need to be assembled, addressing the class-imbalance problem inherent to a comparatively low-incidence outcome such as recurrence [11]. Second, model development should prioritize interpretable architectures — such as gradient-boosted trees with feature-importance visualization — over opaque deep-learning architectures, in line with recommendations for clinical translatability in surgical AI [9, 11].

Third, model performance should be reported using standard discrimination and calibration metrics, including receiver operating characteristic (ROC) analysis with area-under-the-curve (AUC) statistics, sensitivity, and specificity, consistent with methodological standards applied in comparable ophthalmic and otolaryngological prediction models [10, 15]. Finally, prospective external validation across independent surgical centers remains indispensable prior to any clinical deployment, given the well-documented tendency of machine-learning models to lose discriminative performance outside their original training cohort [11].

Robotic and image-guided surgical platforms offer an additional avenue for future integration, as intraoperative data streams could, in principle, be incorporated into a broader AI-assisted surgical planning and prediction pipeline for EDCR, analogous to emerging applications of AI in robotic surgery more generally [12]. Simulation-based training platforms incorporating patient-specific three-dimensional printed models have likewise shown value in preparing surgeons for anatomically complex cases [14], and could plausibly serve as a testbed for validating AI-derived anatomical risk scores before their clinical application.

Conclusion

In summary, although AI-based prediction of recurrence after endoscopic dacryocystorhinostomy remains an emerging rather than established area of investigation, the methodological groundwork developed in adjacent fields — glaucoma surgery [10], refractive surgery [19], head and neck oncology [1, 8, 15], and general otolaryngology [3, 5, 18] — provides a coherent template for its development. A structured, interpretable, and externally validated model integrating preoperative CT-based anatomical features with clinical variables represents a plausible and clinically meaningful direction for future research, with the potential to enable individualized preoperative risk stratification and, ultimately, to reduce the burden of postoperative recurrence in patients undergoing endoscopic dacryocystorhinostomy.

References

1. Alabi R.O., Almangush A., Elmusrati M., Leivo I., Mäkitie A.A. An interpretable machine learning prognostic system for risk stratification in oropharyngeal cancer // *International Journal of Medical Informatics*. – 2022. – Vol. 168. – Art. 104896.
2. Alowais S.A. et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice // *BMC Medical Education*. – 2023. – Vol. 23, № 1. – P. 1–15.
3. Alter I.L., Chan K., Lechien J., Rameau A. An introduction to machine learning and generative artificial intelligence for otolaryngologists-head and neck surgeons: a narrative review // *European Archives of Oto-Rhino-Laryngology*. – 2024. – Vol. 281, № 5. – P. 2723–2731.
4. Asokan A., Massey C.J., Tietbohl C., Kroenke K., Morris M., Ramakrishnan V.R. Physician views of artificial intelligence in otolaryngology and rhinology: a mixed methods study // *Laryngoscope Investigative Otolaryngology*. – 2023. – Vol. 8, № 6. – P. 1468–1475.
5. Bur A.M., Shew M., New J. Artificial intelligence for the otolaryngologist: a state of the art review // *Otolaryngology – Head and Neck Surgery*. – 2019. – Vol. 160, № 4. – P. 603–611.



6. Deka C., Shrivastava A., Nautiyal S., Chauhan P. AI-based automated speech therapy tools for persons with speech sound disorders: a systematic literature review. – 2022.
7. Eichler T. et al. Algorithm-based hearing and speech therapy rehabilitation after cochlear implantation // *Brain Sciences*. – 2022. – Vol. 12, № 5.
8. Esce A.R., Baca A.L., Redemann J.P. et al. Predicting nodal metastases in squamous cell carcinoma of the oral tongue using artificial intelligence // *American Journal of Otolaryngology*. – 2024. – Vol. 45, № 1. – Art. 104102.
9. Habebh H., Gohel S. Machine learning in healthcare // *Current Genomics*. – 2021. – Vol. 22. – P. 291–300.
10. Kailani Z., Kim L., Bierbrier J., Balas M., Mathew D.J. Artificial intelligence for surgical outcome prediction in glaucoma: a systematic review // *Frontiers in Big Data*. – 2025. – Vol. 8. – Art. 1605018.
11. Knudsen J.E., Ghaffar U., Ma R., Hung A.J. Clinical applications of artificial intelligence in robotic surgery // *Journal of Robotic Surgery*. – 2024.
12. Lee C.W., Mantelakis A., Tailor B.V., Khajuria A. Machine learning in otolaryngology-head and neck surgery: a systematic review protocol. – 2020.
13. Mahajan A.P., Shabet C.L., Smith J., Rudy S.F., Kupfer R.A., Bohm L.A. Assessment of artificial intelligence performance on the otolaryngology residency in-service exam // *OTO Open*. – 2023. – Vol. 7, № 4. – e98.
14. Molinari G. et al. Assessment of a novel patient-specific 3D printed multi-material simulator for endoscopic sinus surgery // *Frontiers in Bioengineering and Biotechnology*. – 2022. – Vol. 10. – Art. 974021.
15. Nakajo M., Nagano H., Jinguji M. et al. The usefulness of machine-learning-based evaluation of clinical and pretreatment 18F-FDG-PET/CT radiomic features for predicting prognosis in patients with laryngeal cancer. – 2023.
16. Priel A., Hadida Barzilai D., Tejman-Yarden S. et al. Pre-operative planning of a DCR surgery using virtual reality // *Seminars in Ophthalmology*. – 2025. – Vol. 40, № 1. – P. 35–38.
17. Sarker I.H. Machine learning: algorithms, real-world applications and research directions // *SN Computer Science*. – 2021. – Vol. 2. – Art. 160.
18. Tama B.A., Kim D.H., Kim G., Kim S.W., Lee S. Recent advances in the application of artificial intelligence in otorhinolaryngology-head and neck surgery // *Clinical and Experimental Otorhinolaryngology*. – 2020. – Vol. 13, № 4. – P. 326–339.
19. Varas J., Coronel B.V., Villagrán I. et al. Innovations in surgical training: exploring the role of artificial intelligence and large language models (LLM) // *Revista Colombiana de Cirugía*. – 2023.
20. Zhao X.Y., Chen M., Cheng L. Current and emerging treatment options in sinus and nasal diseases: surgical challenges and therapeutic perspectives // *Journal of Clinical Medicine*. – 2023. – Vol. 12, № 4.