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Transitioning to AI-based Laryngeal Cancer Diagnosis: A Systematic Review

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ABSTRACT

Difficulty with speech, respiration, and deglutition represents a primary clinical presentation in patients diagnosed with laryngeal cancer. Accounting for approximately 1.1 million cases globally, this head and neck malignancy directly impairs the structural and functional integrity of the larynx. Conventional diagnostic and treatment modalities rely heavily on specialized otolaryngological expertise and often carry risks of collateral tissue damage or compromised functional preservation. To mitigate these clinical constraints, artificial intelligence (AI) methodologies have emerged as prominent tools for enabling early detection and precision diagnosis. This systematic review synthesizes literature published between January 2011 and April 2026, mapping the evolutionary trajectory and recent advancements of AI applications in laryngeal oncology. Following PRISMA guidelines, relevant literature was systematically selected and evaluated to highlight methodological developments, identify current clinical limitations, and delineate existing research gaps.

General Terms

Laryngeal Cancer, Artificial Intelligence

Keywords

Laryngeal Cancer, Larynx, Artificial Intelligence, Machine Learning, Deep Learning, CNNs, Optimization Techniques

1. INTRODUCTION

Laryngeal cancer represents the second most prevalent malignancy within the head and neck classification [23], accounting for roughly 20% to 40% of all cases in this domain. Early-stage clinical manifestations typically present as voice hoarseness, persistent sore throat, and palpable cervical lumps [22]. Epidemiologically, the disease predominantly affects individuals over the age of 60, displaying a strong sex disparity with a 4- to 5-fold higher incidence rate in men than in women [39]. Conventional therapeutic strategies rely primarily on radiotherapy and concurrent chemotherapy; however, these procedures demand specialized otolaryngological intervention and often cause severe, long-term morbidity [40]. To address these clinical shortcomings, artificial intelligence (AI) has been increasingly integrated to enable early, real-time diagnostic precision. Specifically, deep learning architectures?most notably Convolutional Neural Networks (CNNs)?have shown promise in analyzing acoustic and vocal signatures for early detection. The primary objective of this review is to evaluate the paradigm shift from conventional clinical practices to modern computational approaches, synthesizing key findings, limitations, and unaddressed research gaps across clinical, AI-driven, and optimization-based literature.

2. BACKGROUND

2.0.1 Imaging in Laryngeal Cancer. Diagnostic imaging works alongside physical examination and tissue biopsy to form the cornerstone of laryngeal cancer evaluation [19]. Standard diagnostic modalities include ultrasonography, endoscopy, histopathology, and cross-sectional radiological imaging, such as computed tomography (CT) and magnetic resonance imaging (MRI). Clinically, ultrasound serves primarily to evaluate cervical lymph node involvement, while endoscopic modalities encompassing standard white-light imaging and narrow-band imaging (NBI) offer high-definition mucosal visualization to improve lesion detection accuracy. Histopathological analysis provides microscopic verification, grading, and structural assessment of the malignancy. Complementing these, radiological cross-sectional imaging is routinely leveraged for precise clinical TNM staging and assessing deep regional lymph node metastasis. Accordingly, this review selectively evaluates literature incorporating at least one primary clinical imaging modality, spanning endoscopic, radiological, histopathological, and ultrasonographic datasets, alongside emerging techniques such as radiomics and stimulated Raman scattering (SRS) microscopy.

3. RELATED WORK

3.0.1 Clinical Diagnosis and Evaluation. Conventional approaches for detecting and managing laryngeal cancer encompass a broad spectrum of diagnostic and surgical interventions. Historically, these manual clinical workflows were time-intensive and relied almost entirely on the subjective expertise of specialized otolaryngologists. Critical evaluation of literature focusing on these traditional strategies reveals several recurrent methodological and clinical constraints. For instance, Agra et al. [1] investigated diagnostic and management protocols in patients who experienced failed initial non-surgical interventions, noting that analysis was limited by substantial heterogeneity in salvage treatment protocols and a heavy reliance on retrospective observational data. In assessing post-operative outcomes, Sotirovic et al. [38] evaluated clinical risk factors associated with surgical site infections; however, their multivariate statistical power was constrained by a small cohort size of infected subjects. Therapeutic trials have also faced practical hurdles; Janssens et al. [16] conducted a Phase III randomized trial comparing accelerated radiotherapy alone against accelerated radiotherapy combined with nicotinamide and carbogen, which demonstrated high operational complexity and a notable risk of minor treatment-related toxicities. Prognostic evaluations present further challenges, as demonstrated by Ferlito et al. [13] in their analysis of mortality causes with an emphasis on second primary malignancies, where accurate survival attribution was confounded by high baseline patient mortality and secondary tumor onset. Regarding organ preservation, Jenckel et al. [17] reviewed state-of-the-art surgical and non-surgical strategies, though their conclusions were constrained by a paucity of long-term functional evidence for emerging robotic and laser salvage techniques. Diagnostic technology trials have similarly yielded mixed results; Westra et al. [37] conducted a randomized trial evaluating whether narrow-band imaging (NBI) offered superior diagnostic efficacy over standard white-light endoscopy for detecting local recurrences, ultimately failing to demonstrate a statistically significant advantage for NBI. In post-operative management research, Wen et al. [44] examined the impact of comprehensive perioperative nursing care, though the study suffered from sample size calculation weaknesses and an overreliance on short-term recovery metrics. Finally, in pre-therapeutic staging, Xia et al. [46] evaluated the utility of high-resolution ultrasonography, identifying key diagnostic limitations caused by acoustic shadowing and poor acoustic penetration through ossified laryngeal cartilages.

3.0.2 *Artificial Intelligence based Diagnosis and Evaluation.*

Conventional clinical analysis of laryngeal cancer presents numerous diagnostic complexities, prompting the integration of artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques to improve early detection and therapeutic precision. However, a critical evaluation of existing AI literature reveals significant technical, architectural, and methodological constraints. Early exploratory efforts, such as the multispectral imaging and Naive Bayesian classification framework developed by Mascharak et al. [25], were heavily bottlenecked by small training cohorts (n=5). Subsequent deep learning systems for real-time classification and localization, including the algorithm introduced by Wellenstein et al. [43], faced data integrity issues due to a lack of histopathological verification in their open-source training subsets. Segmentation and computer vision approaches have also struggled with image-quality artifacts; for instance, the automated vascular analysis framework for narrow-band imaging (NBI) by Barbalata et al. [8] degraded in the presence of submucosal vessels or active bleeding. Similarly, the real-time YOLOv5 model designed by Azam et al. [7] suffered high false-positive rates due to tumor texture variability and the intentional exclusion of benign lesions. Beyond image processing, natural language processing (NLP) applications, such as the social media sentiment analysis by Rao et al. [32], encountered data retrieval limitations and bias from excluding non-English characters. Label-free diagnostic modalities, such as the Stimulated Raman Scattering (SRS) microscopy model proposed by Zhang et al. [50], were constrained by limited fresh surgical tissue access and an inability to stratify tumors into sub-lineages. Prognostic models have faced similar challenges; the deep survival network by Liao et al. [24] lacked external validation and model interpretability due to high computational abstractions. Meta-analyses and systematic reviews underscore these systemic limitations: Du et al. [10] identified substantial study heterogeneity and selection bias across DL-based laryngoscopy literature, while Kaur et al. [21] highlighted poor model generalizability stemming from single-institution training sets. Specialized diagnostic models routinely suffer from dataset reliance or architectural bottlenecks. Rao et al. [31] and Sahoo et al. [35] demonstrated that complex convolutional neural network (CNN) and enhanced Mask R-CNN frameworks were constrained by heavy reliance on proprietary CT datasets and an inability to scale efficiently to larger image repositories. Laryngoscopic classification models, such as the system by Ren et al. [34], restricted their scope to five main conditions, omitting rarer clinical entities like amyloidosis. Similarly, the SegMENT-Plus model by Sampieri et al. [36] exhibited selection bias and a lack of real-world clinical validation, while Kang et al. [20] noted that heavy computational requirements rendered many advanced DL models impractical for resource-limited rural healthcare facilities. Comprehensive literature evaluations by Ezzahori et al. [12] emphasized that extreme database heterogeneity?particularly among vocal acoustic repositories, inhibits standard benchmarking. High operational costs have also hindered adoption, as noted by Wu et al. [45] regarding non-invasive hyperspectral imaging (HSI). Algorithmic interpretation remains a recurrent barrier: Pietruszewska et al. [29] reported that their NBI and white-light diagnostic algorithm struggled with complex pattern recognition in vocal fold leukoplakia, while a systematic review by Alabdalhussein et al. [3] identified severe geographical sampling bias, as most reviewed studies exclusively evaluated Chinese patient cohorts. Classification performance is frequently compromised by architectural or pre-processing flaws, such as suboptimal tumor segmentation in the DenseNet201 model tested by Xu et al. [48] and image blur artifacts affecting the 4-class leukoplakia CNN models evaluated by You et al. [49]. Broader reviews in otorhinolaryngology by Tsilivigkos et al. [41] pointed to a lack of multi-center clinical trials as a primary reason AI models fail in real-world deployment. Scalability and dataset breadth remain persistent bottlenecks: Xiong et al. [47] found that a training corpus of 13,721 laryngoscopic images was insufficient for large-scale clinical deployment, while Rao et al. [30] observed that inconsistent CT acquisition protocols compromised automated anatomical segmentation reliability. Prognostic and survival prediction tools, such as the ML algorithm by Petruzzi et al. [28] (n=132) and the multi-task model by Jang et al. , suffered from restricted applicability to non-surgical cohorts and heavy dependence on manual vocal cord frame selection, respectively. [15] Systematic review findings by Al-Hakami et al. [2] underscored that the opaque, "black box" nature of deep architectures hinders clinical trust when predicting treatment responses. Finally, smaller-scale deep learning models?including the oral and oropharyngeal NBI segmentation network by Paderno et al. [27], the RetinaNet detector by Inaba et al. [14], the binary classification CNNs by Cho et al. [9], the vascular pattern classifier by Esmaeili et al. [11] (n=68), and the edge-computing CNN by Tsung et al. [42], were collectively limited by single-center data acquisition, shadowing artifacts, fixed magnification dependencies, lack of granular disease differentiation, and reliance on single-expert ground-truth annotations.

3.0.3 *Optimization Techniques based Diagnosis and Evaluation.*

Although artificial intelligence-based diagnostic systems have demonstrated remarkable potential in the detection and classification of laryngeal cancer, their performance relies heavily on effective algorithmic optimization and hyperparameter tuning. A critical evaluation of studies employing optimization-driven machine learning and deep learning strategies reveals several recurrent technical and clinical challenges. For example, Mahmood et al. [5] introduced the LCDC-AOADL framework, which leveraged the Aquila Optimization Algorithm to fine-tune a deep belief network for histopathological image classification; however, the model was constrained by its reliance on a single imaging modality and a lack of interpretable Explainable AI (XAI) mechanisms. Similarly, Joseph et al. proposed an early-stage detection approach combining hybrid feature extraction with ensemble learning, though its efficacy was limited by a sc [18]arcity of annotated medical datasets and precise tumor margin segmentation. Metaheuristic optimization techniques frequently introduce severe computational overhead: the framework designed by Alazwari et al. [4], which combined SE-ResNet feature extraction with an adaptive sparrow search algorithm, suffered from high computational complexity and extended optimization runtime. Likewise, Mohamed et al. [26] integrated EfficientNet-B0 with a dwarf mongoose optimization algorithm, which achieved accurate classification but incurred substantial training times and high processing loads. In another ensemble optimization attempt, Alzakari et al. [6] utilized a dandelion optimizer for hyperparameter tuning, but the pipeline remained heavily dependent on rigorous image pre-processing and exhibited high structural complexity during training. Finally, preprocessing optimization efforts, such as the hyperspectral image processor developed by Regeling et al. [33] to correct noise and spatial misregistration, were fundamentally bottlenecked by limited cohort sizes (n=25).

4. METHODOLOGY

To ensure a rigorous and transparent evaluation of relevant literature, this systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The search strategy specifically targeted studies leveraging machine learning and deep learning methodologies for laryngeal cancer applications published over a 15-year period, spanning from January 2011 through April 2026. Following systematic identification, screening, and eligibility evaluation, a total of 172 studies met the predefined inclusion criteria for full synthesis. The step-by-step literature search, identification, and selection workflow is illustrated in the PRISMA flow diagram as depicted in Figure 1. In the initial identification phase of the PRISMA method, as shown in Fig 1, encompassed from January 2011 to April 2026 and it brought about 172 studies. The division of studies across different databases (sources) was as follows: 116 studies were collected from PubMed, 12 studies from IEEE Xplore, 28 studies were collected from Springer, and 16 studies were collected from Science Direct/ Elsevier. In the screening phase, 16 duplicates were eliminated from the initial search results. After removing 16 studies 156 studies remained. of the remaining studies were subsequently assessed, which resulted in 137 articles remaining. During the inclusion stage, the eligibility of the remaining 137 articles was thoroughly examined. After reviewing 87 articles were excluded for not being satisfying inclusion criteria or having incomplete results. Out of 172 articles 50 article satisfied the eligibility criteria for inclusion.

5. LITERATURE COLLECTION

Research papers were collected from different databases like Institute of Electrical and Electronics Engineers (IEEE) Xplore, PubMed, Springer and Science Direct/ Elsevier, and Taylor and Francis. The summary is presented through table 1. Additionally, figure 2 and figure 3 shows the studies in duration time period. Moreover table 2 represents the inclusion and exclusion criteria for the studies considering for the literature review.

6. DISCUSSION

6.1 Overview and Categorization

A comprehensive range of diagnostic paradigms for the identification and evaluation of laryngeal cancer has been systematically analyzed in this review. Adhering to PRISMA guidelines, literature published across a 15-year window (January 2011 to April 2026) was systematically surveyed, yielding 50 primary studies that evaluate algorithmic frameworks for laryngeal cancer detection. Based on methodological focus, the selected studies were categorized into three core domains:Clinical Diagnosis and Evaluation Artificial Intelligence-Based Diagnosis and Evaluation Optimization Technique-Based Diagnosis and Evaluation The relative distribution of included studies across these three thematic domains is illustrated in Figure 4.
As illustrated in Figure 4, the majority of recent literature centers on artificial intelligence-based frameworks (69%), followed by optimization-driven strategies (18%) and traditional clinical evaluations (13%). Synthesis of these studies indicates that deep learning architectures integrated with metaheuristic optimization algorithms represent the most predominant and high-performing technical strategy in recent literature.
Multi-Modal Comparative Analysis Diagnostic tools for laryngeal cancer vary depending on the visual or acoustic data processed:

—**White Light Imaging (WLE):** Standard WLE gives doctors a quick, non-invasive look at laryngeal anatomy. Convolutional networks trained on WLE handle broad binary tasks well (such as separating normal tissue from abnormal growth). They struggle, however, to distinguish early-stage carcinoma in situ from benign conditions like vocal fold leukoplakia because mucosal surface differences can be faint.

—**Narrow Band Imaging (NBI):** NBI highlights intraepithelial papillary capillary loops (IPCLs) in mucosal tissue. Because of these clear microvascular cues, CNNs trained on NBI outpace WLE algorithms in accuracy and specificity. These models are helpful for spotting premalignant lesions and distinguishing them from early invasive squamous cell carcinoma.

—**Radiological Imaging (CT / MRI):** Volumetric CT and MRI scans processed by models like Mask R-CNN or 3D DenseNet focus on spatial staging, pre-treatment TNM classification, and deep anatomical mapping. While these tools map cartilage invasion and regional lymph node involvement, their diagnostic accuracy hinges on scan resolution, slice thickness, and precise radiologist annotations.

—**Vocal Acoustics & Phonatory Signals:** Models analyzing acoustic traits (such as MFCCs, jitter, or shimmer) or utilizing 1D-CNNs look for voice degradation tied to vocal fold mass effects. Acoustic testing provides a fast, low-cost screening option well-suited for telemedicine, though its specificity drops when trying to separate early glottic tumors from benign conditions like polyps or laryngitis.

—**Stimulated Raman Scattering (SRS) Microscopy:** SRS microscopy enables rapid, label-free intraoperative histopathology. Deep learning classifiers reading SRS images offer high diagnostic accuracy by measuring nuclear density and protein-to-lipid ratios directly from fresh tissue samples. Adopting SRS broadly

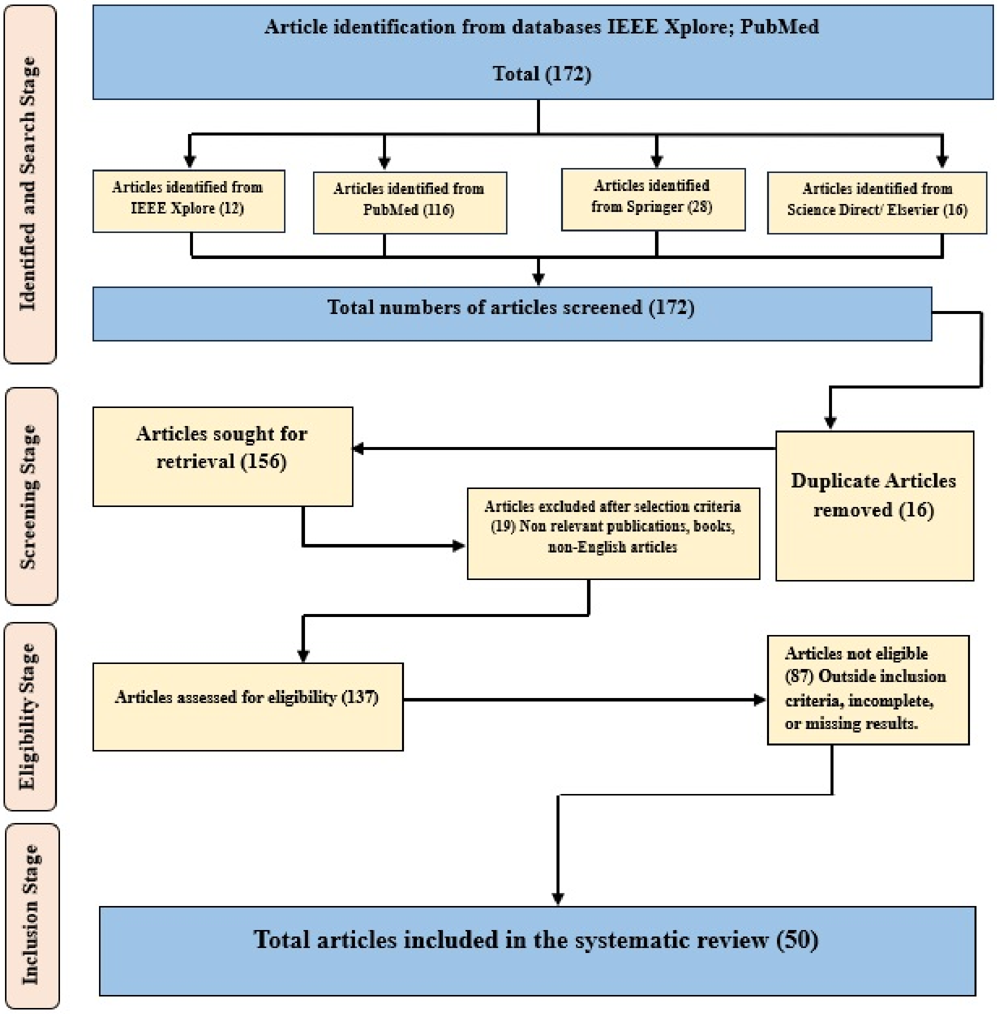

Fig. 1. Flow diagram of PRISMA approach used for systematic review.

Table 1. Categorization of Retrieved Studies from IEEE Xplore, and PubMed

Sources	Number of Research paper	Number of Review Paper	Article/Letter	Total No. of studies
IEEE Xplore	12	0	0	12
PubMed	99	16	1	116
Springer	19	9	0	28
Science Direct/ Elsevier	15	1	0	16

remains difficult due to equipment costs and limited access to large intraoperative datasets.

6.2 Scenario and Dataset Stratification

Early-Stage vs. Advanced-Stage Laryngeal Tumors Deep learning performance shifts across clinical cancer stages. Advanced T3–T4 tumors, which cause obvious structural distortion, are flagged by vision models with high accuracy (¿95%). Early T1–T2 glottic cancers present subtle epithelial modifications that lead to higher false-negative rates. Combining metaheuristic hyperparameter optimization with attention mechanisms helps models focus on granular vascular IPCL patterns rather than overall throat geometry, boosting sensitivity for early-stage cases. **Sensitivity to Clinical Image Artifacts** Image artifacts often degrade model performance in real-world clinical settings:

—**Submucosal Vessels & Active Bleeding:** Bleeding or prominent submucosal vessels change expected color gradients, causing models like YOLOv5 or Mask R-CNN to misidentify lesion boundaries.

—**Acoustic Shadowing from Ossified Cartilage:** Cartilage calcification creates acoustic shadowing in CT and ultrasound scans, obscuring deep tumor boundaries and complicating automated segmentation.

Table 2. Inclusion and Exclusion Criteria of the Review

Inclusion Criteria	Exclusion Criteria
Studies using CNN for laryngeal cancer detection.	Studies published prior to 2011 were excluded.
Studies using machine learning focus on laryngeal cancer classification and detection.	Studies focusing on biological mechanisms were excluded.
Studies that used at least one form of medical image modality.	Studies focusing on voice analysis were excluded.
Studies comparing different models.	Papers other than English language were excluded.
Peer-reviewed journal articles published within the selected time frame (2011?2026).	Blogs and papers which are not currently peer-reviewed.
Research reporting quantitative evaluation metrics.	Non-human studies, such as animal research, were excluded.
Studies focusing on optimization techniques (natural or mathematical) were included.	Studies focusing on more than one data modality were excluded.

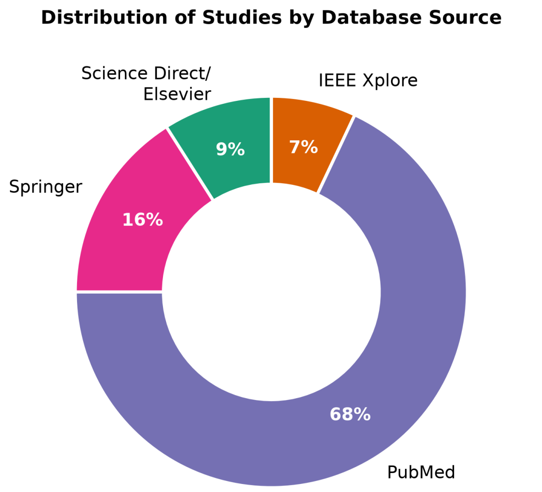

Fig. 2. Illustrating the number of collected studies from 2011 to 2026 (till April 2026).

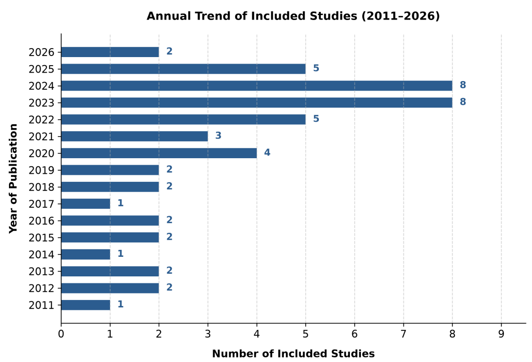

Fig. 3. Illustrating the number of annual studies included after satisfying the inclusion criteria from 2011 to 2026 (till April 2026).

—**Image Motion & Blur:** Rapid vocal fold movement during videolaryngoscopy introduces motion blur, which disrupts fine-grained multi-class classification.

6.3 Multi-Center vs. Single-Center Generalizability

Single-center training remains a primary vulnerability for current laryngeal AI tools. Algorithms trained on data from a single hospital often suffer performance drops of 10% to 15% when tested

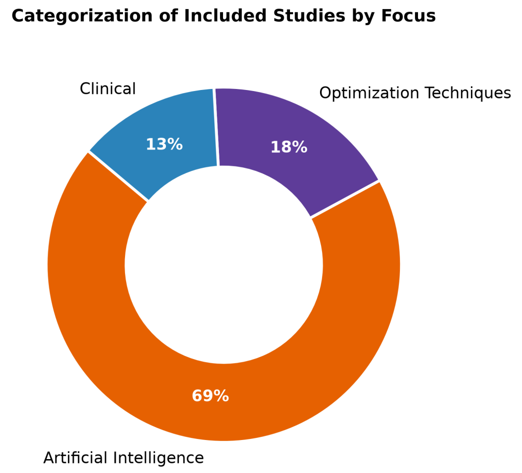

Fig. 4. Proportional distribution and classification of included studies across clinical, artificial intelligence, and optimization domains.

on external cohorts. Discrepancies in camera brands, light sources, compression formats, and patient demographics hurt external generalizability. Multi-center external validation and federated training methods are necessary steps toward clinical deployment. Figure 5 illustrates the primary clinical and technical challenges that currently limit the translational adoption of AI models in laryngeal oncology.
As depicted in Figure 5, addressing the "black box" nature of these computational models—which lack transparency, interpretability, and clinical explainability—remains paramount. Overcoming these barriers is essential to establish clinical trust for real-world automated decision-making.

6.4 Quantitative Performance Synthesis Across Paradigms

Table 3 compares representative computational models across clinical, deep learning, and optimization paradigms, highlighting key validation metrics alongside primary operational limits.

7. CONCLUSION

Over the past fifteen years (2011-2026), the diagnostic paradigm for laryngeal cancer has undergone a profound transformation, evolving from manual, observer-dependent clinical evaluations to automated, AI-driven computational frameworks. This systematic review has mapped this evolutionary trajectory, highlighting how modern deep learning architectures have largely superseded traditional workflows by eliminating the need for handcrafted feature

Table 3. Performance Summary of Representative AI and Optimization Frameworks in Laryngeal Cancer Diagnosis

Paradigm / Strategy	Representative Authors & Year	Model Architecture / Method	Data Modality	Cohort Size / Dataset Scope	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	Key Limitations / Operational Constraints
Clinical / Acoustic	Mascharak et al. (2018)	Naïve Bayesian Classifier	Multispectral / NBI	$n = 5$ patients	∼82.0%	80.0%	83.3%	—	Extremely small sample size; lacks generalizability.
Clinical / Acoustic	Cho et al. (2022)	1D-CNN Acoustic Framework	Vocal Pathological Signals	Voice Recordings	85.0%	78.0%	93.0%	—	Elevated false positives when evaluating benign vocal fold lesions.
Deep Learning	Azam et al. (2022)	Real-time YOLOv5 Detector	WLE & NBI Endoscopy	Videolaryngoscopy frames	88.5%	86.2%	89.1%	0.910	High false-positive rates driven by texture variation; omits benign lesions.
Deep Learning	Xu et al. (2023)	DenseNet201 Framework	Laryngoscopic Images	Multi-center dataset	86.3% (Ext.)	84.1%	88.0%	0.920	Performance drop on external test sets; imperfect tumor boundary segmentation.
Deep Learning	Sahoo et al. (2022)	Enhanced Mask R-CNN	CT Radiological Images	Proprietary CT Scans	91.4%	90.2%	92.1%	0.942	Tied to single-institution scan protocols; high computational demands.
Deep Learning	Zhang et al. (2019)	ResNet-based SRS Classifier	SRS Microscopy	Fresh Surgical Tissue	94.2%	93.8%	95.0%	0.982	Requires fresh intraoperative tissue; cannot differentiate specific tumor sub-types.
Optimization	Alazwari et al. (2024)	SE-ResNet + Adaptive Sparrow Search	Laryngeal Images	Biomedical Image Repository	96.8%	95.9%	97.2%	0.978	Heavy metaheuristic computational load; extended search times.
Optimization	Mahmood et al. (2023)	Aquila Optimization + Deep Belief Net	Histopathology	Throat Region Images	97.1%	96.5%	97.5%	0.983	Limited to single data modalities; lacks Explainable AI (XAI) features.
Optimization	Mohamed et al. (2023)	EfficientNet-B0 + Dwarf Mongoose	Endoscopic Images	Throat Images	97.8%	97.1%	98.2%	0.989	High training memory requirements and slower optimization convergence.

extraction and enabling rapid, real-time diagnostic screening. By categorizing the existing literature into three core domains?clinical evaluation, artificial intelligence methodologies, and optimization-driven strategies?this synthesis provides a critical appraisal of current capabilities alongside their methodological constraints. While deep learning models consistently demonstrate superior diagnostic accuracy compared to conventional clinical methods, their translational efficacy remains heavily governed by neural network architecture, training dataset diversity, and hyperparameter optimization. A central insight derived from this review is the critical role of advanced optimization techniques in refining model convergence, enhancing generalization, and mitigating overfitting in complex clinical datasets. Moving forward, addressing key barriers such as dataset heterogeneity, limited model interpretability, and high computational demands will require close multidisciplinary collaboration between computer scientists and clinical otolaryngologists. By overcoming these operational challenges, future research can foster the deployment of accurate, interpretable, and equitable AI tools for laryngeal cancer screening, ultimately improving early detection rates and patient prognosis on a global scale.

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