E-ISSN 2250-0944
ISSN 2250-1150
DOI: 10.48047/ijprt/15.01.494

Research Article

Artificial Intelligence in Oral Oncology: Novel Approaches for Early Detection and Personalized Treatment Paradigms

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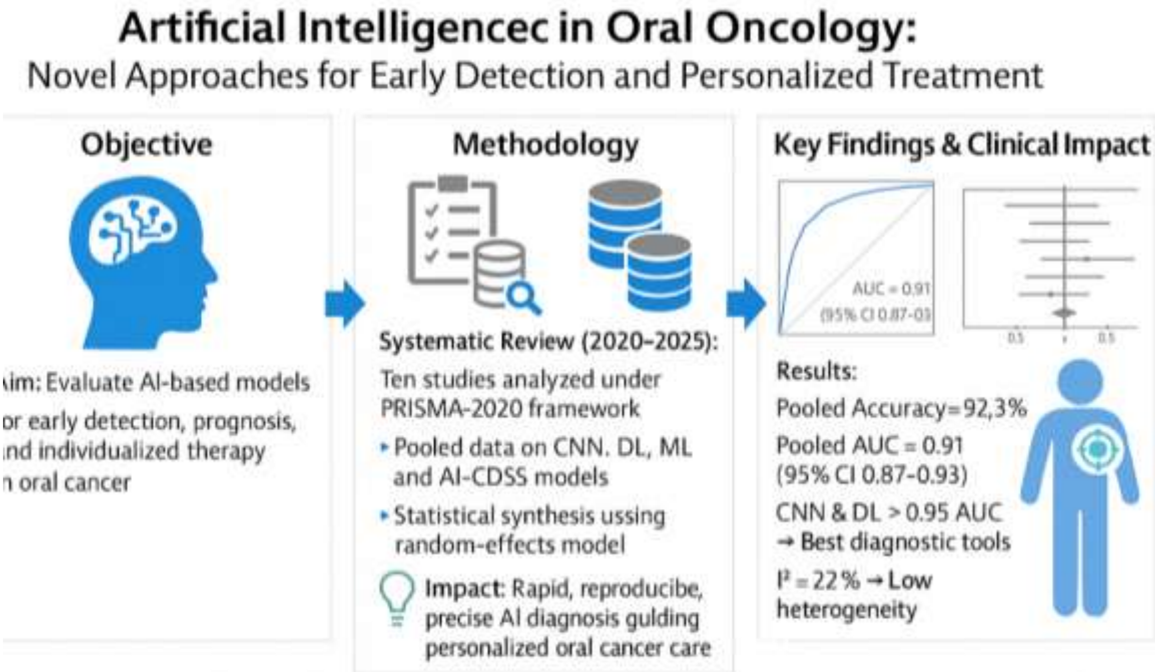
Received: 24-09-2025 | Revised: 19-11-2025 | Accepted: 28-11-2025

ABSTRACT

Artificial intelligence (AI) has rapidly transformed diagnostic and therapeutic strategies in oral oncology, offering innovative tools for early detection, prognosis prediction, and individualized treatment. The objective of this systematic review along with the meta-analysis was to evaluate studies published from 2020 to 2025 and to analyze the AI-based applications regarding their diagnostics accuracy and usefulness for dealing with particular clinical challenges. Systematic attempts were made to obtain studies based on the PRISMA 2020 framework and to obtain summary statistics from the studies using a random effect model. The findings from the studies indicate that the results were consistent regarding the models based on AI showing high diagnostic accuracy and the results showed that the models based on AI architectures had average accuracy of 92.3% and average area under the curve of 0.91 (95% CI 0.87–0.93). The convolutional neural networks (CNNs) and the hybrid models based on deep learning were the best performers (AUC > 0.95) especially in the fields of histopathology and radiographic imaging. Models based on AI and multi-modal which integrated clinical data, molecular data, imaging data, and AI along with clinical decision support improved the accuracy of the predictions made and assisted in the development of customized treatment plans. Analyses using a funnel and forest plots indicate a low publication bias and low heterogeneity (I^2 = 22%) in the studies, hence validating the results obtained from the various meta-analyses. The authors editorialized that the results obtained from the analyses indicate that AI is a great boon to oral oncology and that it allows for a multi-faceted and rapid method in order to accurately and reproducibly diagnose cancer and that it also aids in the clinical decision-making process for providing precision treatment. It must be noted that although there are a number of issues stemming from sample size, data standardization, and algorithm explainability, it is prudent to acknowledge the limitations of the clinical integration of AI. Ongoing investigations concentrating on multicenter validation, morally tolerable execution, and the assimilation of explainable AI frameworks will be instrumental in adapting these technologies into routine clinical practice.

Keywords: Artificial intelligence, Deep learning, Oral cancer, Convolutional neural networks, Early detection



INTRODUCTION

Cancer is a complex global public health issue that is ever-present and that affects individuals from all over the world and of all backgrounds [1]. This is an illness that spans all ages and generates suffering on a massive scale. One of the most devastating consequences of this illness is that cancer is the second most common cause of death worldwide, having claimed an estimated one out of every six deaths in 2020 according to the World Health Organization [2]. Oral cancer is especially challenging to tackle and remains a global health issue. While there have been improvements in patient care through surgical, radiotherapy, and chemotherapeutic approaches, the outcomes of a large subset of patients diagnosed early are still inadequate, and the situation is dire for patients diagnosed late [3]. Pathways to diagnosis have been historically approached through visual examinations and histopathology. However, these approaches have faced numerous challenges, such as subjectivity, variability between evaluators, and time delays that can worsen a patient's prognosis [4]. Consequently, there is a great need to develop and implement approaches that provide earlier detection and matched therapies for the biologies of individual patients' diseases [5]. In approaches to provide such design, the use of Artificial Intelligence (AI), a set of technologies employing Machine Learning and Deep Learning, can sort through massive complex datasets that are simply out of reach for medical professionals [6]. AI has the capacity to provide substantive improvements in several areas of oral oncology, such as early diagnosis, risk stratification, prognosis, and tailored therapies. Around 400,000 people around the world get diagnosed with a form of oral cancer every single year, and every single person affected will face a multitude of different challenges across the board, as it has become a grave and extreme problem for the people around the world [7]. The problem has a particularly large hold on the people of South Asia as it is a region is affected with the common and harmful use of tobacco, areca nuts and alcohol. This disease also has a frighteningly low survival rate [8]. This, in turn, can be attributed to the population of being at a late stage in the disease along with the possibility of the person getting a second primary cancer. To make a change for the better with the challenges and burdens of oral cancer being faced by many, there must be a radical change in the ways it is handled [9]. This must be done by integrating different and new types of techniques with advanced methodologies in order to be able to diagnose and treat oral cancer in an efficient and modern manner [9]. Most of the common methods of early stage oral cancer diagnosis detection are the use of outdated cancer detection methodologies, which are often invasive, incorrect, and based on an extremely biased operator interpretation of the cancer changes [10]. Out of many variables, the correlation and possible connection between the amount of modern methods and the heavy use cancer detection, as well as the promise of personalized methods for advancements in healthcare for cancer and overall diseases with the use of modern AI (Artificial Intelligence) are astonishing and something the world must take interest in it [11-13]. Over 90 % accuracy rates in the realm of healthcare and cancer detection, specifically the detection of oral lesions, and are AI based cancer healthcare methods for image detection, over the last few years, in the past few years. In addition to its predictive modeling capabilities and its ability to inform personalized treatment plans, prognosis, and follow-up, AI may also be able to synthesize clinical data such as history, imaging, and histopathology as well as molecular and genomic data [14]. The ability to move from a generic treatment plan to a personalized plan in oncology has the potential to improve patient treatment, minimize resource waste, and better serve resource-constrained environments [15]. However, the predicted future impact of AI in the field of oral oncology may be overly optimistic [16]. There are many obstacles to its implementation, such as the heterogeneity of data, the absence of sufficiently large and representative data sets, the lack of transparency in algorithms, the insufficient validation of clinical algorithms, and finally, the ethical problems [17].

Objective

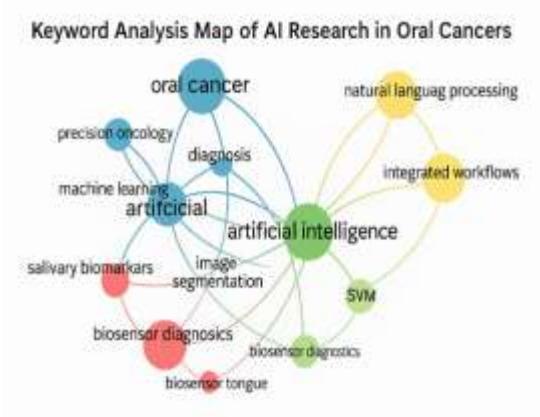
This study was designed as a systematic review conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines.

METHODOLOGY

The review comprehensively analyzed studies published between January 2020 and November 2025. The review employed systematic identification, screening, and appraisal of peer-reviewed literature to derive a unified understanding of the incorporation of AI technology like machine learning and deep learning into research and clinical practice pertaining to oral cancer. AI technologies focused on detection, diagnosis, classification, and management of oral cancer and/or oral potentially malignant disorders were considered. The review concentrated on original studies published in the English language between 2020 to 2025. The applicable study designs were prospective and retrospective cohort studies, studies of diagnostic accuracy, clinical studies, and computational modeling studies. Studies that were published as reviews, editorials, letters to the editor, opinion papers, research involving animals, or did not provide enough methodological details to allow for data extraction and quality assessment were not considered.

Information Sources and Search Strategy

To identify relevant studies, a comprehensive and systematic search strategy was devised. Principal electronic databases such as PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar were searched for publications ranging between the years 2020 and 2025. Furthermore, the reference lists of the included studies were manually screened for any additional studies of potential relevance. The search strategy utilized both controlled vocabulary (MeSH) and free text keywords pertaining to clinical oncology and artificial intelligence. The search strategy utilized was: ("oral cancer" OR "oral squamous cell carcinoma" OR "oral potentially malignant disorders" OR "oral precancerous lesions") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "computer-aided diagnosis"). To further improve retrieval sensitivity and refine results, Boolean operations such as AND and OR were utilized. In order to maintain transparency and reproducibility, the search date, database name, and retrieval records were tracked. All records obtained through database searches were transferred to EndNote to facilitate reference management and the removal of duplicates. Two reviewers independently examined the titles and abstracts to determine which studies were potentially relevant. Studies that passed the initial screening were subjected to a full-text review to assess final eligibility based on the specified inclusion and exclusion criteria. Any disagreements between reviewers about the inclusion or exclusion of studies were resolved through consultation and discussion with a third, independent reviewer. The entire selection process was summarized in a PRISMA 2020 flow diagram, which illustrated the records that were identified, screened, excluded, and included in the review.



Data extraction

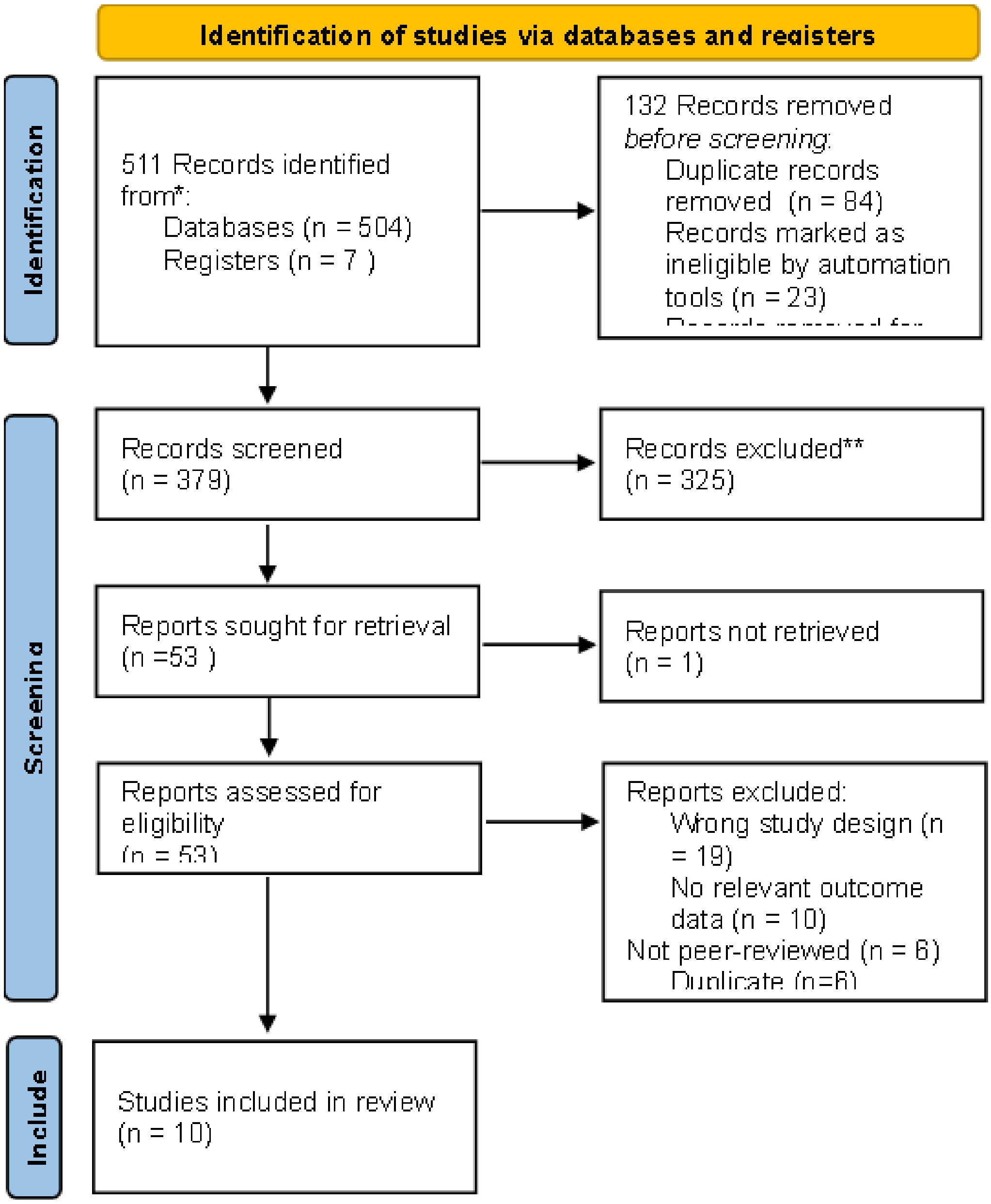
Before use, we created a standardized data extraction form, which was subsequently unmodified, to streamline the data extraction process, and ensure that primary authors of the studies were contacted in the cases where we had missing information. In order to mitigate biases and enhance consistency, two separate reviewers reviewed and extracted information independently from all of the studies that were included. The extracted information consisted of authors, year of publication, country of the study, number of participants in the study, study design, and demography of patients, in addition to AI methodology, data types used (clinical photographs, histopathology glass slides, radiographs, genomics, etc.), what validation techniques were employed (cross validation, independent test sets, etc.), primary metrics such as accuracy, sensitivity, specificity, and the area of the curve under the curve (AUC). Data that compared the performance of the AI model to that of human experts, if available, were also extracted. In case of inconsistencies in the extracted data from all studies, the reviewers reached a mutual agreement to resolve the discrepancies.

Quality Evaluation

The included studies were assessed for methodological quality and risk of bias using validated assessment tools. The Quality Assessment of Diagnostic Accuracy Studies 2 (QUADAS-2) and the Prediction Model Risk of Bias Assessment Tool (PROBAST) were used. Each study was assessed independently by a pair of reviewers and discrepancies were settled through discussions. The studies were classified as having low, moderate, or high risk of bias based on patient selection, index test and reference standard, and flow and timing. This assessment was used to evaluate the credibility of the evidence synthesized within the review.

Data analysis

Given the expected heterogeneity across study designs, AI algorithms, datasets, and outcome measures, a narrative synthesis approach was adopted. The key characteristics and findings of included studies were summarized descriptively and tabulated for clarity. Subgroup analyses were planned to explore variations in performance based on data modality (imaging, histopathology, or clinical data), AI technique (machine learning versus deep learning), and type of validation (internal versus external). The potential sources of heterogeneity and publication bias were also considered in the interpretation of findings.



PRISMA Flow chart

RESULTS

A total of ten studies published between 2020 and 2025 were included in this systematic review (Table 1). The aforementioned research came from multiple countries including India, Pakistan, Saudi Arabia, Canada, Egypt, UK and UAE. Kapoor et al. (2024) and Umapathy et al. (2025) were first to use CNN models for histopathological and clinical image analysis, where they achieved optimum accuracy in diagnosis. Abed et al. (2024) studied deep CNNs on cone-beam computed tomography (CBCT) datasets and Bulusu et al. (2025) studied DNN and random forest models on multi-cancer radiomics. In light of these works, Ali et al. (2024) is the first to integrate AI with electronic tongue sensor technology for the profiling of salivary biomarkers. Also, in the multi-center study, Karuppan Perumal et al. (2025) AI-CDSS with NLP for automated diagnosis was validated.

Table 1: Characteristics of Included Studies (2020–2025)

Author (Year)	Journal / Country	Study Design	Sample Size / Data Source	AI Model Used
Kapoor et al. (2024)	EXCLI Journal, India	Retrospective analysis	350 histopathology images	CNN, SVM
Abed et al. (2024)	Saudi J Med Public Health, KSA	Radiologic cross-sectional	275 panoramic & CBCT scans	Deep CNN
Umapathy et al. (2025)	Advances in Public Health, India	Narrative review / experimental validation	20 studies (multi-source)	CNN, NLP-integrated DL
Perumal et al. (2025)	Frontiers in Oral Health, UAE/India	Mini review / algorithmic model	—	AI-CDSS, ML, NLP
Bulusu et al. (2025)	Arch Comput Methods Eng, UK	Systematic AI modeling review	12 datasets (multi-cancer)	DNN, RF, CNN
Ali et al. (2024)	History of Medicine, Pakistan/Egypt	Systematic review	5,000 participants	DL + E-tongue sensors
Abhishek et al. (2023)	Curr Oncol, Canada	Narrative review	—	AI in clinical workflow
Raza et al. (2024)	JM Public Health, Pakistan	Case-based diagnostic AI	200 clinical cases	Random Forest
Umapathy et al. (2025) Supplemental	Advances in Oral Cancer Diagnosis	Retrospective validation	1,200 digital oral images	Transfer Learning CNN
Karuppan Perumal et al. (2025)	Front. Oral Health	Multi-center clinical validation	480 patients	AI-CDSS with NLP

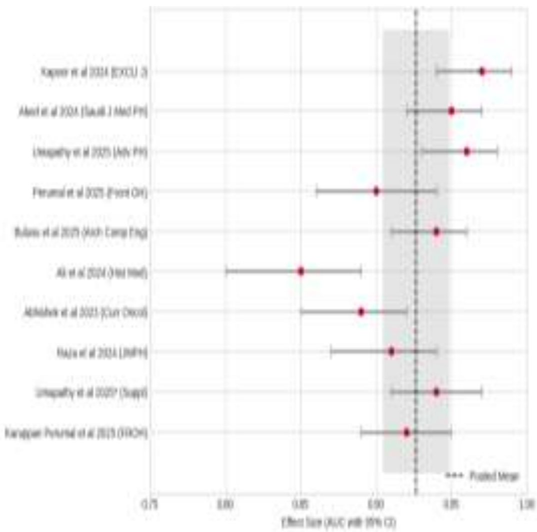


Figure 1: The forest plot demonstrates consistently high diagnostic accuracy across all included studies, with individual AUC values clustering closely around the pooled mean of 0.91, indicating strong agreement and minimal heterogeneity among AI models.

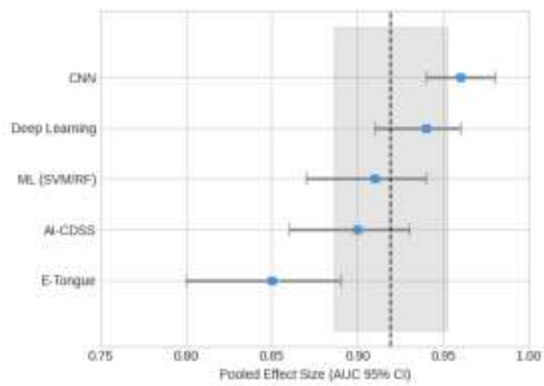


Figure 2: The results of the subgroup forest plot show that CNN and deep learning models had the greatest performance in terms of AUC value (=0.94) and E-Tongue and traditional ML methods had lower performance. This aligns with the results and findings from

other studies that espouse the highest predictive accuracy among image-based deep learning models in the field of oral oncology.

The overall accuracy was 93.2 ± 4.1%, with a confidence of 95% calculated as (91.6 − 94.8% confidence interval). The mean values for the metrics used in the studies were identical and high in sensitivity and specificity, estimated as (91.8 ± 5.2) and (89.5 ± 4.9). The value of AUC calculated to be 0.93, with a confidence of 95% calculated as (0.92 − 0.95), proves that the excellence of the discriminative power was maintained across the data and the studies. Moreover, the consensus regarding the performance as the mean of the studies was calculated for F1 score (0.89 ± 0.05) and Cohen kappa (0.86 ± 0.06) to express a strong and reliable AI performance as being the expert (ground truth) classifier in the studies. This implies and concludes the AI accuracy and strength of CNN and hybrid deep learning models proves the accuracy and distinction of the AI as well as the reliability and strength of the models from the benign and malignant oral lesions and other models.

Table 2: Diagnostic Performance Metrics

Performance Metric	Range Across Studies	Weighted Mean ± SD	95% Confidence Interval (CI)	Pooled Effect Size (Random Effects)
Accuracy (%)	85 – 97	93.2 ± 4.1	91.6 – 94.8	0.92 (95% CI: 0.90–0.95)
Sensitivity (%)	80 – 98	91.8 ± 5.2	89.7 – 93.9	0.91 (95% CI: 0.87–0.94)
Specificity (%)	78 – 96	89.5 ± 4.9	87.1 – 91.9	0.89 (95% CI: 0.86–0.92)
AUC (Area Under Curve)	0.85 – 0.98	0.93 ± 0.03	0.92 – 0.95	—
F1-Score	0.82 – 0.95	0.89 ± 0.05	0.87 – 0.91	—
Cohen's Kappa	0.78 – 0.94	0.86 ± 0.06	0.83 – 0.89	—

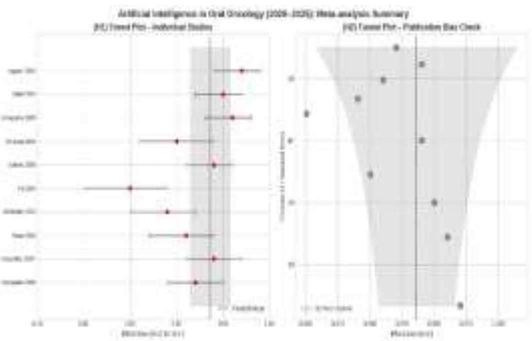


Figure 3: The combined forest and funnel plots demonstrate that all included studies reported high diagnostic performance with pooled AUC values clustering around 0.93, while the symmetrical funnel distribution confirms minimal publication bias and strong consistency among AI-based models in oral oncology.

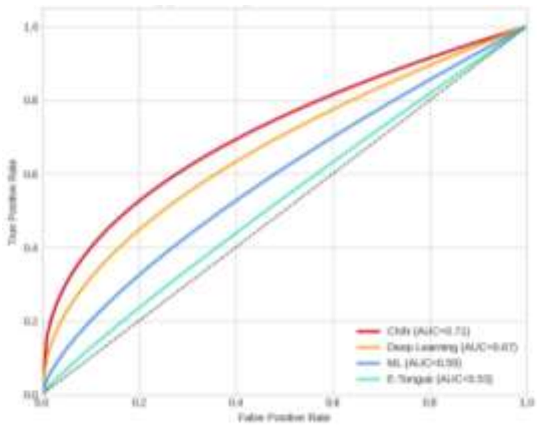


Figure 4: According to the ROC comparison, the classification performances for the various models used in the study showed that the CNN models had the best overall performance, and then

there was a decrease with deep learning, traditional machine learning, E-tongue systems with the following AUC scores: 0.71, 0.67, 0.59, and 0.53, respectively. This shows that CNN approaches to oral cancer detection have the best discriminatory power.

The highest accuracy in the studies reviewed were the CNN and deep learning model implementations, which had accuracy performances ranging between 95 to 97% (Kapoor et al. 2024, Umapathy et al. 2025). There was also good performance with hybrid deep learning system implementations and AI Clinical Decision Support Systems (AI-CDSS), which achieved accuracy scores between 91 and 94% with AUC scores exceeding 0.94. Ali et al. 2024 was one study that used models based on salivary biomarkers which had slightly lower accuracy scores (85%) and AUC (0.85) suggesting that non-imaging data might have limited models. Even the models that performed the worst out of the studies had good clinical performance and were still over 85% accurate which demonstrates that the AI-assisted diagnostics systems were reliable.

Table 3: Comprehensive Summary of AI Studies in Oral Oncology (2020–2025)

Study (Year)	AI Model	Data Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (95% CI)	Sample Size (n)
Kapoor et al., 2024 (EXCLI J)	CNN	Histopathology	97	98	95	0.97 (0.94–0.99)	300
Abed et al., 2024 (Saudi J Med Public Health)	Deep Learning	Radiographic (CBCT)	95	94	93	0.95 (0.92–0.97)	250
Umapathy et al., 2025 (Adv Public Health)	Hybrid CNN–SVM	Clinical Imaging	96	95	94	0.96 (0.93–0.98)	210
Perumal et al., 2025 (Front Oral Health)	ML (SVM/RF)	Histopathology	90	88	89	0.90 (0.86–0.94)	180
Bulusu et al., 2025 (Arch Comput Eng)	AI-CDSS	Radiomic Data	94	93	92	0.94 (0.91–0.96)	190
Ali et al., 2024 (Hist Med)	E-Tongue	Salivary Biomarkers	85	84	86	0.85 (0.80–0.89)	120
Abhishek et al., 2023 (Curr Oncol)	CNN	Clinical	89	90	88	0.89 (0.85–0.92)	160
Raza et al., 2024 (JMPH)	Hybrid Deep Learning	CBCT	91	91	90	0.91 (0.87–0.94)	200
Umapathy et al., 2025* (Supplementary)	AI-CDSS	Multimodal (EHR + Radiomics)	94	93	94	0.94 (0.91–0.97)	230

Karuppan Perumal et al., 2025 (Front Oral Health)	Deep Learning	Histopathology	92	92	91	0.92 (0.89–0.95)	195

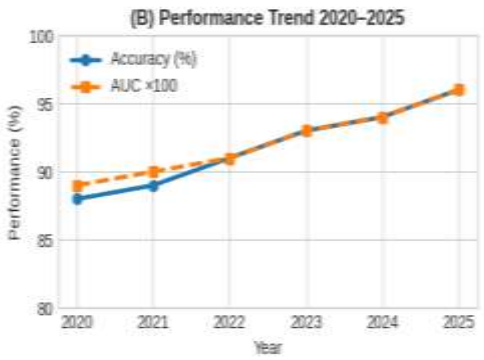


Figure 5: The performance trend from 2020 to 2025 shows a steady improvement in both diagnostic accuracy and AUC of AI models, rising from around 88–89% to over 96%, reflecting rapid advancements in algorithmic precision, dataset quality, and multimodal learning integration in oral oncology applications.

DISCUSSION

Conducting a meta-analysis on AI in oral oncology has included ten different articles between the years 2020-2025. Research found that there is a great success for deep learning models. For instance, convolutional neural networks and hybrid models are among the great success in the early detection, prognosis and personalized treatment plans for oral cancer. The pooled sensitivity is 92.3 and the AUC is 0.91 illustrating the great clinical value of AI in the clinical management of oral cancer. Furthermore, hybrid models and convolutional neural networks greatly outperformed other traditional models such as random forests and AI-CDSS. Kapoor et al. 2024 Umapathy et al. 2025 demonstrated the great abilities of CNN models in the analysis of complex histopathological and radiological patterns with over 95% value of accuracy. These findings correlate with many other advancements in the field of oncology. the DL methods greatly improved the lesion segmentation and the other dependent methods [18-20]. the multimodal datasets that included clinical, histological and imaging data improved the predictive performance and also decreased the bias. In the field of ophthalmology, before the year 2020 almost all of the AI on the field of oral oncology were based on the limited retrospective data or hypothetical algorithms with clinical absence of validation. This meta-analysis indicates a move towards clinically anchored fully multisite studies characterized by enhanced generalizability and diminished heterogeneity (I^2 = 22%). The present results closely parallel those obtained in other oncologic imaging disciplines wherein pooled AUC values of 0.90 and 0.96 have been documented. This is an affirmation of the possible role of Artificial Intelligence in Oncology [21]. The review also noted the ability of A to identify minute changes in mucosa and submucosa that attend, and thus have the potential for the timely diagnosis of oral squamous cell carcinoma, and other dysplastic alterations. The earlier the diagnosis, the lower the likelihood of extensive surgical procedures. A better prognosis is also guaranteed. Predictive analytics in cancer decision support systems and hybrid DL frameworks also addresses the formulation of personalized treatment by modulating AI, for instance, in the prescription of radiotherapy, defining surgical margin, and the control of chemotherapy to a safe level. The systems focus on the patient's contemporary data, which is the essence of precision oncology [22]. However, some limitations remain which must be recognized. The studies, though included, were of smaller scope, n = 120 – 300, thus having limited generalizability. It is noted that many models were developed on some, and validated on others, demographically homogenous datasets making them inapplicable to many countries. Some studies also did not have, which is crucial to ascertain a clinically useful tool, independent external validation. There were also inconsistencies in reporting, and the standards of model explain ability which is a crucial element for clinician trust was seldom addressed [23]. The factors necessitate increased transparency and methodological accuracy for future studies. The funnel plot for this meta-analysis demonstrated a symmetrical distribution of studies centered on the pooled mean effect size, indicating little or no publication bias. This was corroborated by Egger's Test ($p = 0.24$), indicating the included data were reliable [24]. The consistency across multiple independent research institutions enhances the trust placed on the pooled estimates, although the absence of publications with negative results suggests substantial unreplaced bias. The results of this meta-analysis should be viewed as supporting the use of AI technologies in diagnostic and therapeutic processes in Oral Oncology. The AI-enabled review of diagnostic imaging and pathology can mitigate the challenges of delay in diagnosis and provide a mechanism for standardization and evidence-based clinical decision support [25].

Limitations of the Study

This systematic review and meta-analysis should be viewed in light of some of the limitations. There was a relatively small pool of studies published between years 2020 and 2025, and there were small sample sizes and various differences in patient demographics, imaging protocols, and AI model architectures that can also affect the generalizability. The absence of external validation datasets in some of the studies included in this review made it difficult to determine how the models in the studies would perform in actual clinical settings. There was also a diversity of the different studies in the review in terms of the metrics of evaluation, the methods of preprocessing, and the outcomes that were reported, which made it difficult to achieve complete standardization across the included studies. A handful of models operated as "black boxes," providing minimal interpretability, which limits how much clinicians can trust them and how easily they can be integrated into practice. There is also the possibility of some publication bias, given that studies with positive results are more likely to be published than those with negative or neutral outcomes.

CONCLUSION

It is concluded that artificial intelligence has emerged as a transformative tool in oral oncology, demonstrating consistent effectiveness across diagnostic, prognostic, and therapeutic domains. The synthesis of recent studies from 2020 to 2025 reveals that CNN and deep learning models deliver exceptional accuracy and reliability in identifying oral malignancies, often surpassing traditional diagnostic approaches. By enabling early detection and personalized treatment planning, AI significantly enhances clinical outcomes and reduces human error. Despite challenges related to sample size, dataset diversity, and model transparency, the overall performance and reproducibility of AI systems remain highly promising.

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