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ARTIFICIAL INTELLIGENCE: A BOON TO UNTANGLE THE DIFFICULTIES IN REDUCING THE BURDEN OF ORAL CANCER: A SYSTEMATIC REVIEW AND META-ANALYSIS

Seema Sharad Salve ^{1,*}, Gautam Bhagwan Sawase ¹, Pandit Laxmanrao Killarikar ¹ and Suhani Milind Mali ²

¹ Rural Health and Training Centre, Paithan, India.

² ACPM Dental College, Dhule, India.

* Corresponding Author

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ABSTRACT

Oral Cancer (OC) is sixth most common cancer worldwide with increased mortality and morbidity. Early diagnosis increases the 5-year survival rate to 83%. Hence early detection acts as a key strategy for prevention and control of OC.

In recent years, Artificial Intelligence (AI) has emerged as a promising tool for improving the accuracy and efficiency of disease diagnosis. AI can precisely analyze enormous dataset from different modalities which in turn may potentially improve OC screening. With this context a systematic review was conducted to explore the role of AI in various diagnostic approaches for oral precancer and cancer.

Objectives:

- To identify, assess, and summarize the testimony for reported uses of AI in the areas of oral cancer
- To evaluate the arrays of AI in histopathology, imaging, cytology and genomics
- To see the robustness of AI in screening, early diagnosis, prognostic prediction, treatment planning and prevention of OC

Methods: Adhering to PRISMA guidelines, the review scrutinized literature published between 1-3-2015 to 28-02-2025 from PubMed, Scopus, and EMBASE databases with key words as Oral Cancer, Cytology, Genomics and Artificial Intelligence. Studies were screened first for eligibility based on inclusion and exclusion criteria. Details of the study included and data was extracted.

Results: Qualitative data was analyzed for assessing sensitivity, specificity and heterogeneity of various AI techniques among studies with similar outcomes.

Conclusion: This review and meta-analysis intuit that AI combined with traditional approaches marks the significant breakthrough in healthcare innovation reducing the burden of eminently preventable OC.

Keywords: oral cancer, artificial intelligence, deep learning, machine learning

1 INTRODUCTION

Oral cancer (OC) remains a major global public health challenge, ranking as the sixth most common cancer worldwide and accounting for significant mortality and morbidity [1, 2]. A major contributor to the poor overall prognosis of OC is late-stage presentation, which heavily limits therapeutic efficacy and patient survival [2]. When detected at an early, localized stage (Stage I or II), the 5-year relative survival rate increases significantly to approximately 83%, compared to less than 40% when diagnosed after distant metastasis has occurred [2, 3]. Consequently, early detection and timely intervention represent the paramount control strategies for reducing OC-related disease burden and improving patient outcomes [3, 4].

In recent years, Artificial Intelligence (AI)—encompassing machine learning (ML) and deep learning (DL) architectures—has emerged as a transformative clinical tool capable of enhancing diagnostic precision, efficiency, and decision-making [4, 5]. AI algorithms excel at evaluating complex, high-dimensional datasets across diverse healthcare modalities, including clinical photography, histopathological slides, radiological imaging, cytology, and genomic profiles [5, 6]. By automating pattern recognition and capturing subtle pathological feature variations that may escape manual visual inspection, AI-driven platforms offer substantial potential to standardize screening, eliminate inter-observer variability, and refine risk stratification [4, 6].

With this context, this systematic review was conducted to evaluate the clinical effectiveness, diagnostic accuracy, and multi-modal applications of AI models in oral cancer detection, prognostic evaluation, and survival rate prediction across varied operational domains.

2 MATERIAL AND METHODS

This systematic review and meta-analysis was conducted in strict adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [1]. The primary research question driving this review was: *"What are the arrays and efficacy of AI in oral cancer diagnosis and predicting its prognosis?"* The protocol was structured using the PICO framework as follows:

- **Population (P):** Patients evaluated for oral precancer and cancer, utilizing datasets comprising clinical photographs, radiological images, histological slides, and genomic data.
- **Intervention (I):** Application of artificial intelligence (AI)-based models, including machine learning and deep learning architectures, for the diagnosis, screening, and prognostic prediction of oral cancer and precancerous conditions.
- **Comparison (C):** Conventional diagnostic approaches, professional clinical insights, and established reference benchmarks.
- **Outcomes (O):** Quantitative performance metrics including diagnostic accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC).

2.1.1 Search Strategy and Databases

A comprehensive literature search was executed across three major electronic databases: PubMed, EMBASE, and Scopus, spanning publications from March 1, 2015, to February 28, 2025. Keywords utilized in combinations with Boolean operators ("AND", "OR") included: *Artificial intelligence, oral cancer diagnosis, oral cancer prognosis, Deep learning, and machine learning.*

2.1.2 Study Selection and Screening Process

The study selection flow followed a systematic screening procedure:

- **Initial Identification:** A total of 936 records were identified from the database searches.
- **Deduplication:** 472 duplicate records were excluded, leaving 464 articles for preliminary screening.
- **Availability Screening:** 256 paywalled/purchase-restricted articles were excluded, yielding 208 articles for full screening.
- **Title & Abstract Screening:** 208 records were screened for thematic relevance, leaving 81 reports to be assessed for full-text eligibility.
- **Eligibility Evaluation:** After evaluating full texts against strict selection criteria, 36 studies fulfilled all requirements and were included in the systematic review.

2.1.3 Inclusion and Exclusion Criteria

- **Inclusion Criteria:** Full-length, peer-reviewed original research articles published in English; studies featuring quantitative data analysis; and research directly investigating AI applications in oral cancer or precancer.
- **Exclusion Criteria:** Retracted articles, conference abstracts, letters to the editor, case reports, general literature reviews, paywalled/purchase articles, and publications in non-English languages.

2.1.4 Data Extraction and Quality Assessment

For the 36 included studies, detailed data were extracted using a standardized collection sheet. Extracted variables included study identification, sample size, dataset characteristics (clinical, radiological, histological, genomic), specific AI/ML algorithms evaluated, outcome indicators (sensitivity, specificity, accuracy, AUC), and prognostic parameters.

3 RESULTS

Across the 36 eligible studies, artificial intelligence (AI) framework implementation spanned two clinical domains: primary disease detection/diagnosis and prognostic evaluation (recurrence risk stratification and overall survival prediction). Data modalities encompassed clinical photographs, histopathological whole-slide images, cytological smears, and genomic sequence profiles. Algorithmic architectures evaluated included machine learning (ML), deep learning (DL), and multi-modal hybrid models.

3.1 Diagnostic Performance & Meta-Analysis

Meta-analysis calculated pooled estimates for sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC), demonstrating strong overall diagnostic efficacy:

- **Algorithmic Hierarchy:** Multi-modal hybrid approaches yielded the highest diagnostic accuracy, followed by deep learning architectures and traditional machine learning models.
- **Subgroup Efficacy:** Deep learning models processed on histopathological whole-slide images outperformed conventional ML across most metrics, achieving an overall pooled accuracy of 94.1%.
- **Lesion-Wise Classification:** AI algorithms demonstrated significantly higher diagnostic accuracy and specificity when classifying overt oral cancer compared to oral potentially malignant disorders (OPMDs).
- **Heterogeneity, Risk of Bias & Publication Bias**

3.1.1 Forest Plot Analysis:

Forest plots illustrated notable variance in sensitivity, specificity, and AUC estimates across included studies.

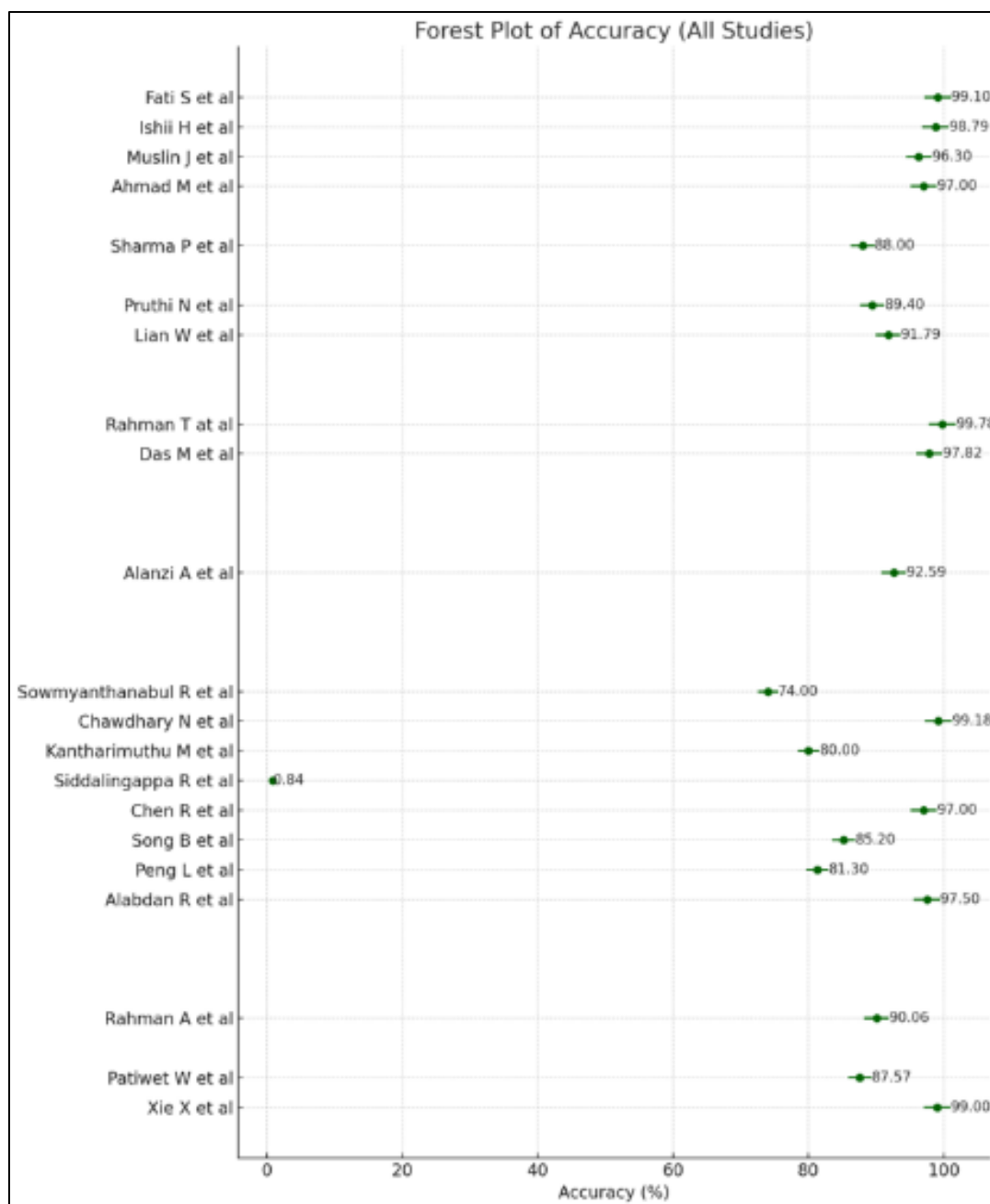


Figure 1: Forest Plot Analysis (Accuracy)

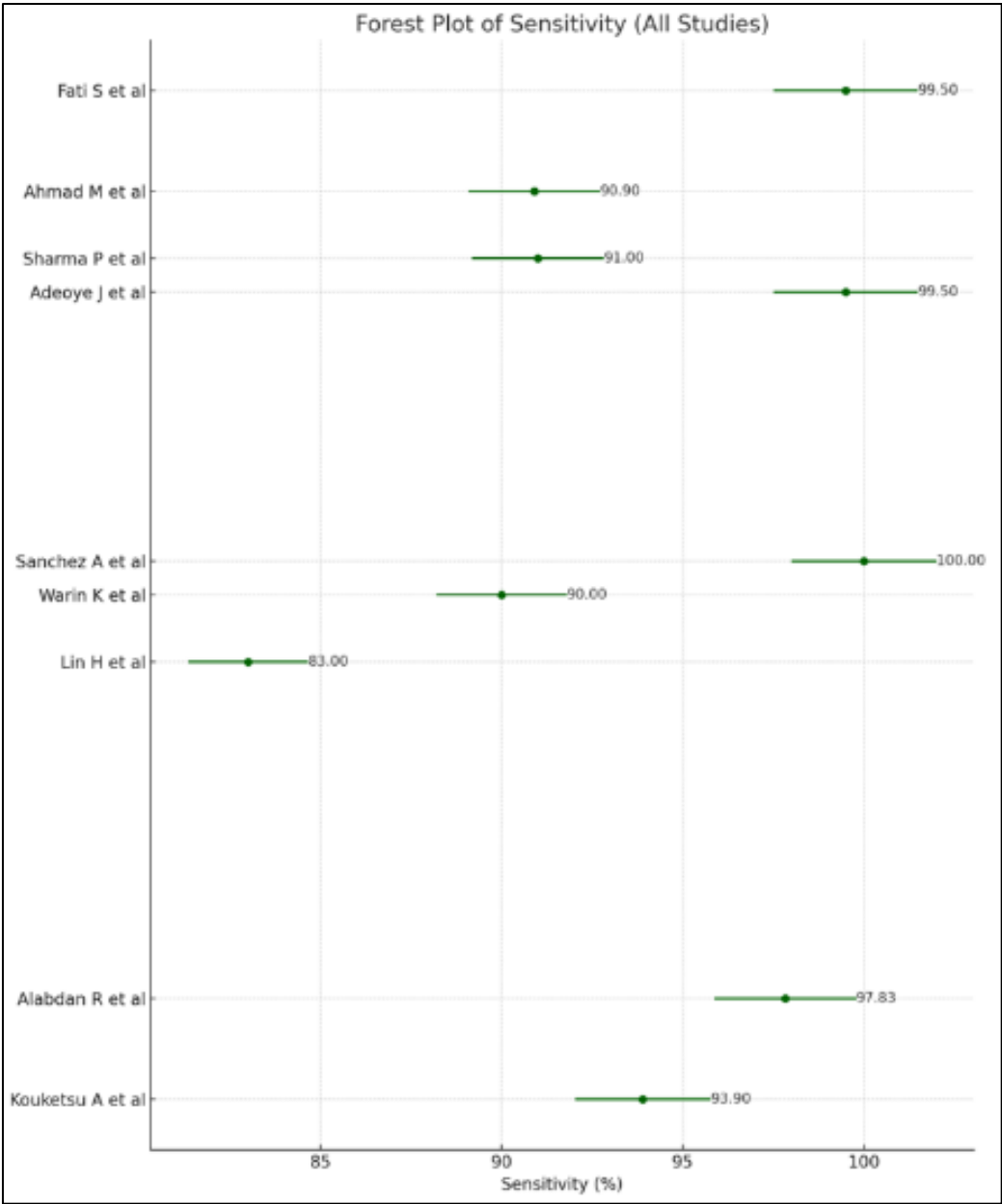


Figure 2: Forest Plot Analysis (Sensitivity)

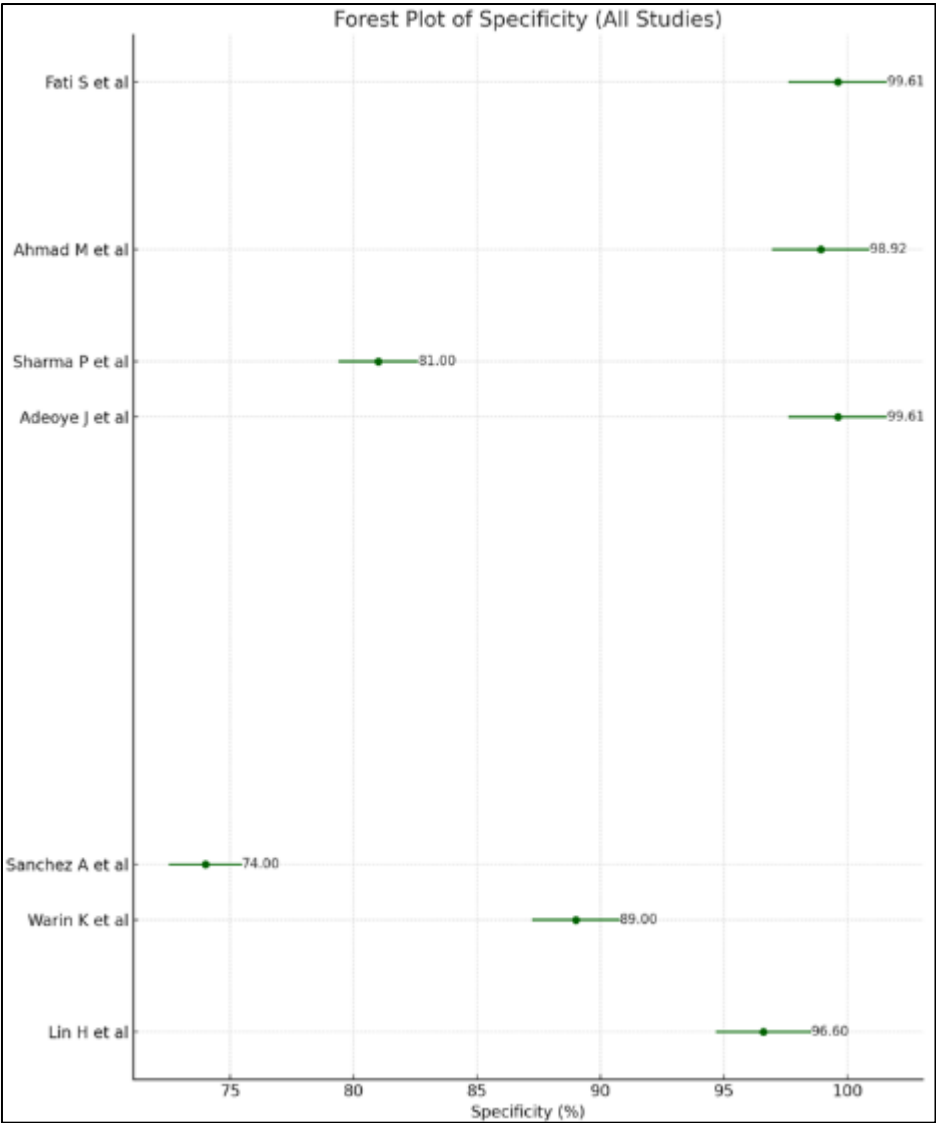


Figure 3: Forest Plot Analysis (Specificity)

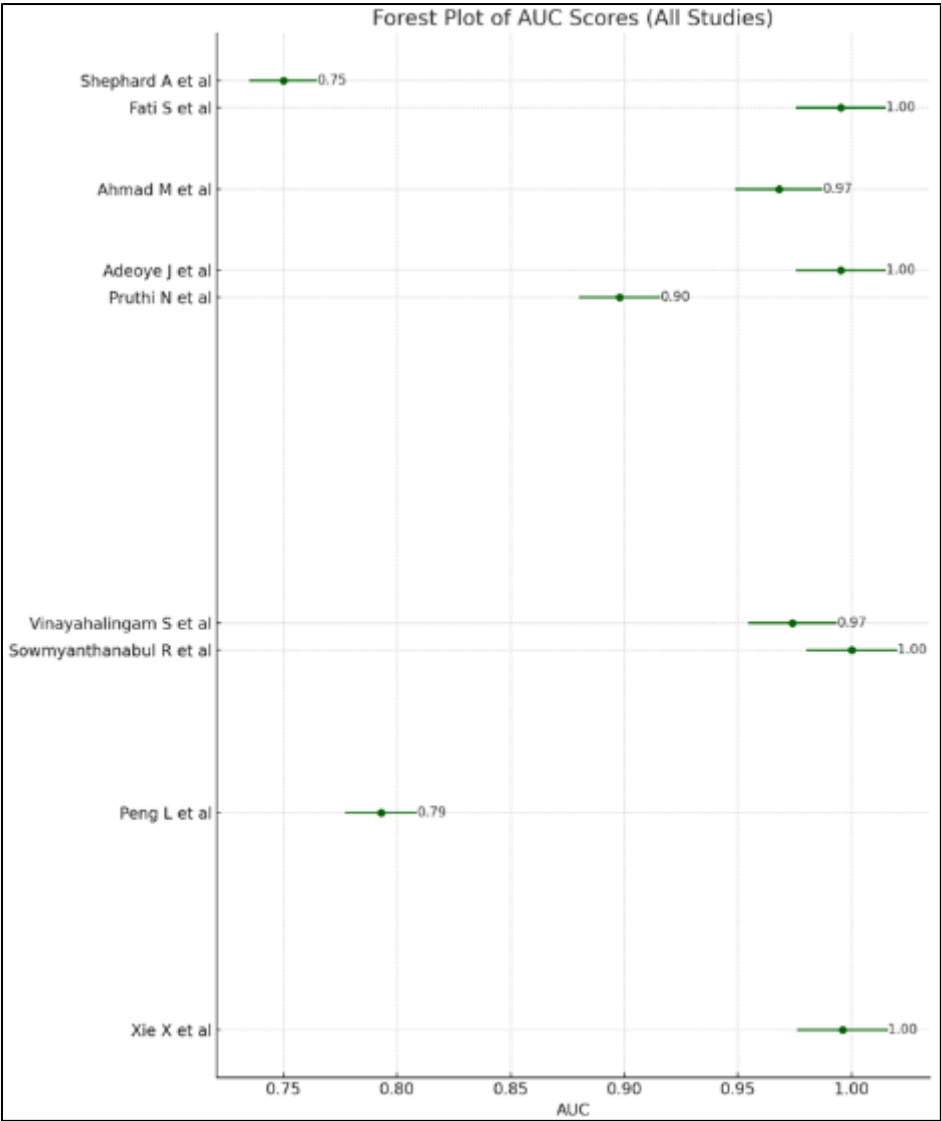


Figure 4: Forest Plot Analysis (AUC Curve)

3.1.2 Study Quality & Bias:

Risk of bias assessments revealed high or unclear risk of bias alongside substantial statistical heterogeneity (I^2) across the evidence base, signaling a need for standardized protocols.

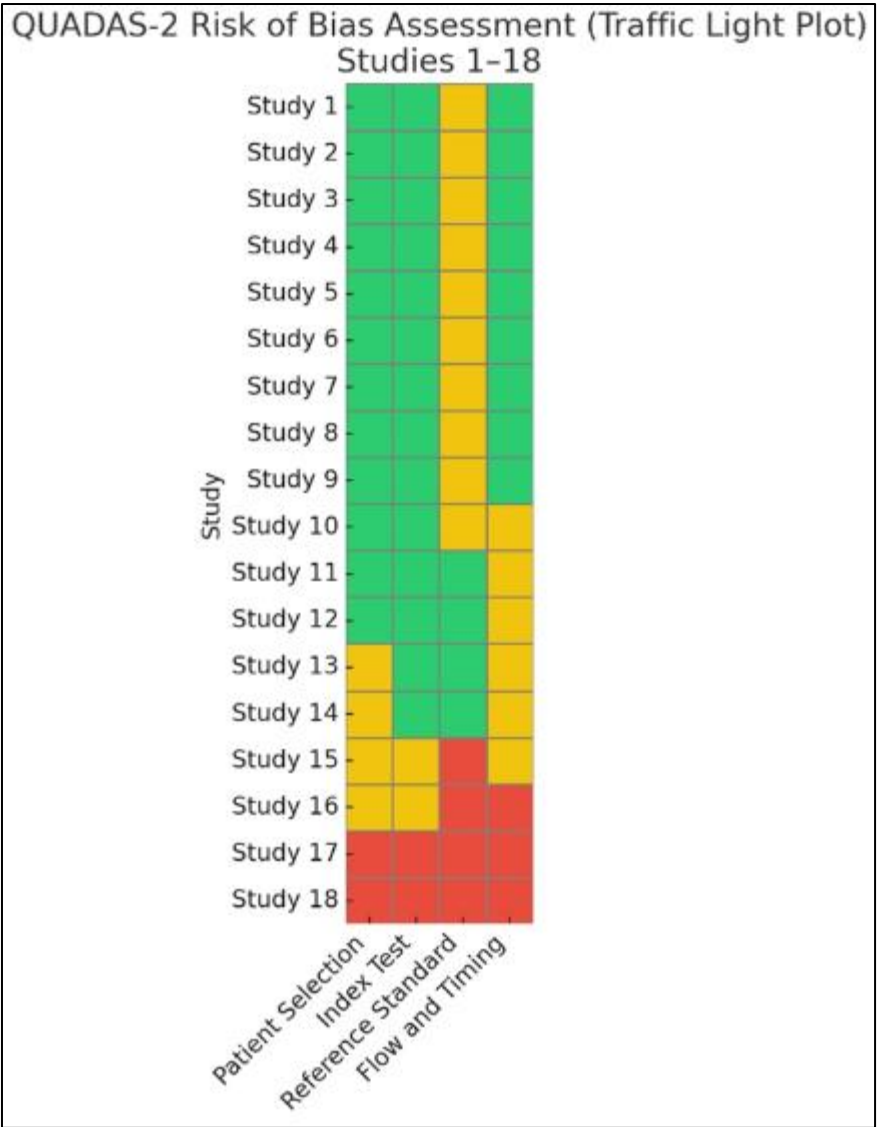


Figure 5: Risk of Bias Assessment- Traffic Light Plot of Studies 1-18 (Green: Low, Yellow: Unclear, Red: High)

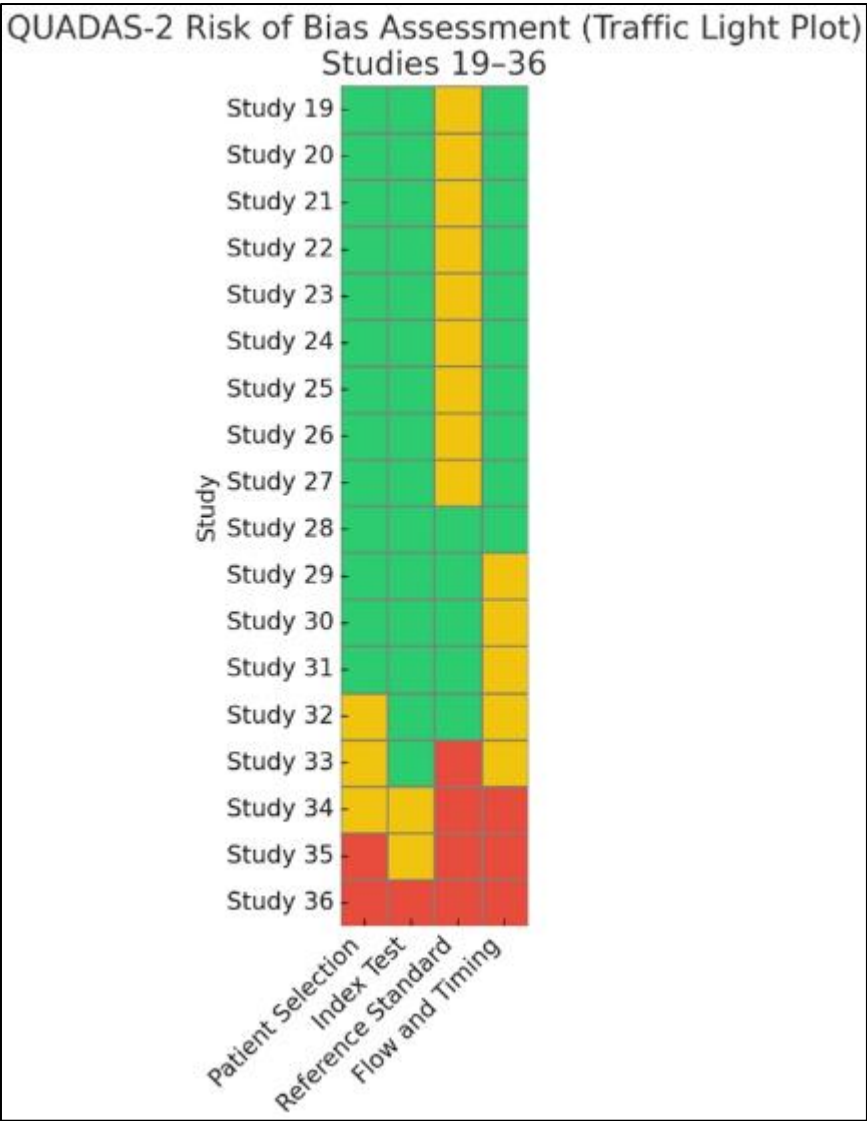


Figure 6: Risk of Bias Assessment- Traffic Light Plot of Studies 19-36 (Green: Low, Yellow: Unclear, Red: High)

3.1.3 Funnel Plot Analysis:

Visual inspection of funnel plots across all 36 studies revealed asymmetry, indicating publication bias and marked study heterogeneity.

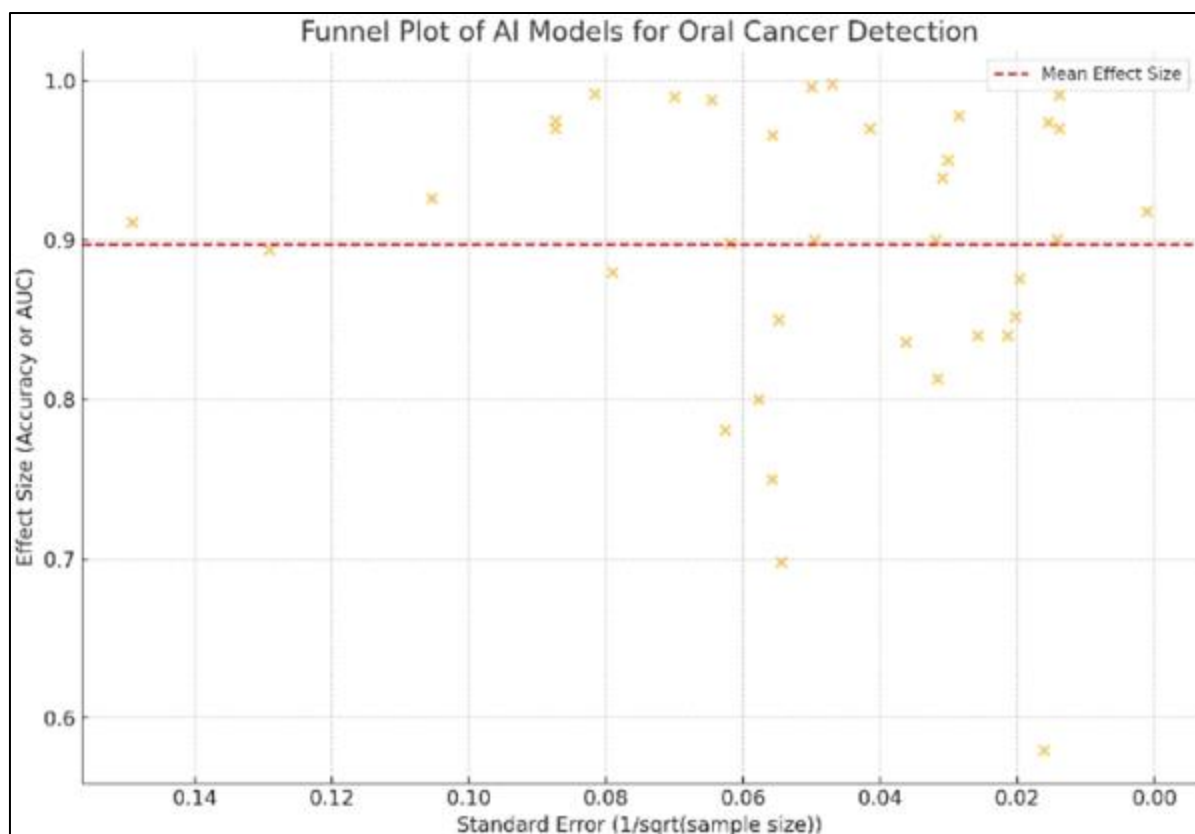


Figure 7: Funnel Plot Analysis For Oral Cancer Detection

4 DISCUSSION

The clinical management of oral cancer (OC) remains heavily constrained by high rates of late-stage presentation, which significantly compromise patient prognosis and long-term survival rates [1-3]. These poor clinical outcomes stem primarily from opportunistic, highly subjective screening practices and substantial delays in therapeutic initiation [1-3]. AI-driven computational models directly address these diagnostic bottlenecks by identifying subtle, sub-visual pathological variations, leveraging diverse high-dimensional data streams, and offering objective decision support [4-6].

The findings of this meta-analysis strongly align with prior literature, confirming AI's exceptional diagnostic performance across clinical, radiological, histological, and genomic modalities [7-10]. Diniz-Freitas et al. (2022) previously demonstrated pooled sensitivity and specificity metrics exceeding 85% when utilizing image-based datasets for OC screening [7]. Similarly, Asif et al. (2023) established the superior capability of deep learning frameworks applied to histological whole-slide images (WSIs) [8]. These findings are corroborated by primary studies in present synthesis, such as Fati et al., who achieved a diagnostic accuracy of 99.1% with an AUC of 0.995 [9], and Ahmad et al., who reported an overall classification accuracy of 97% [10].

Across the evaluated studies, researchers implemented a wide spectrum of AI frameworks—ranging from classic machine learning (ML) to deep learning (DL) and multi-modal hybrid networks [4, 5]. Deep learning architectures (specifically Convolutional Neural Networks) demonstrated superior diagnostic accuracy in automated image classification and precise lesion segmentation compared to conventional ML algorithms [5, 6]. Moreover, multimodal imaging and information fusion strategies substantially improved diagnostic precision by resolving clinical ambiguities inherent to single-modality evaluations [5, 6].

Recent developments highlight a clear architectural evolution from traditional Convolutional Neural Networks toward advanced deep learning platforms [4, 6]. Frameworks such as Vision Transformers—demonstrated by Vinayahalingam et al. (2024) [11]—and hybrid deep learning systems—as evaluated by Sowmyanthanabul et al. (2024) [12]—outperform legacy models by capturing complex long-range dependencies and generating feature-rich representations of tissue microenvironments and genomic profiles [11, 12]. Furthermore, studies by Volmer et al. (2024) [13] and Lian et al. (2025) [14] underscored the paramount importance of intermediate multimodal data fusion, showing that cross-modal data integration yields superior predictive robustness and generalizability.

Despite these promising breakthroughs, notable methodological limitations persist across the literature [4]. Risk of bias assessments identified frequent high or unclear risk of bias, particularly concerning reference standard selection as well as patient flow and timing protocols [4]. Additionally, widespread heterogeneity in performance metrics creates significant barriers to cross-study comparison and standardization [4]. To overcome these challenges and facilitate routine clinical integration, future research must prioritize standardized reporting (such as STARD-AI guidelines), create open-access annotated public datasets, and develop explainable AI (XAI) models tailored for seamless workflow integration in resource-limited, high-burden settings [4-6].

5 CONCLUSION

Artificial intelligence comprising deep learning, and image fusion techniques represent a transformative shift in oral cancer oncology. By enabling objective pattern recognition, automated segmentation, and cross-modality feature synthesis, these computational paradigms directly address historical barriers related to delayed diagnosis and subjective screening. While preliminary retrospective evaluations highlight exceptional diagnostic accuracy, routine clinical deployment hinges on overcoming significant methodological challenges, including study bias, metric heterogeneity, and data imbalance. Future advancements must focus on constructing standardized multi-centre datasets, ensuring external prospective validation, and implementing explainable AI frameworks. Ultimately, integrating robust AI algorithms into point-of-care workflows holds profound potential to democratize early oral cancer detection, optimize clinical decision-making, and improve patient survival outcomes globally.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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