

AI-Powered Diagnostic and Treatment Approaches for Oral Cancer Using CNN and Medical Imaging: A Comprehensive Review

Priti Nirgun Shinde¹ and Dr. Brijendra Gupta²

ME Student, Siddhant College of Engineering, S. P. Pune University, Pune, Maharashtra¹

Associate Professor, Siddhant College of Engineering, S. P. Pune University, Pune, Maharashtra²

Abstract: Oral cancer continues to pose a critical global health challenge, particularly in low- and middle-income countries where tobacco, alcohol consumption, and poor oral hygiene are predominant risk factors. Traditional diagnostic methods, though widely used, often suffer from invasiveness, subjectivity, and delays, thereby limiting their effectiveness in early detection. Recent advancements in Artificial Intelligence (AI), especially Convolutional Neural Networks (CNNs) integrated with multimodal imaging (MRI, CT, PET), have revolutionized diagnostic approaches. This review conducted a bibliometric and thematic analysis of global research contributions from 2013–2025, highlighting publication growth, influential studies, methodological frameworks, and clinical applications. Results demonstrate that AI-powered systems outperform or complement clinical experts in accuracy, sensitivity, and risk stratification, offering transformative potential for diagnosis, treatment planning, and monitoring. Despite significant progress, challenges remain in standardizing datasets, achieving clinical validation, and ensuring large-scale implementation. The findings underscore AI's growing role in predictive oncology while emphasizing the urgent need for translational research and policy integration.

Keywords: Oral Cancer, Artificial Intelligence, Convolutional Neural Networks, Early Detection, Medical Imaging

I. INTRODUCTION

Oral cancer represents a significant global health challenge, ranking among the top 10 most prevalent cancers worldwide. According to the World Health Organization (WHO), more than 300,000 new cases of oral cancer are diagnosed annually, with a disproportionately high incidence in low- and middle-income countries due to tobacco use, alcohol consumption, and poor oral hygiene. The prognosis of oral cancer is strongly correlated with the stage at diagnosis: early-stage detection dramatically improves the 5-year survival rate, whereas advanced-stage diagnoses often result in poor patient outcomes and limited treatment options. Traditional diagnostic approaches, including visual inspection and histopathological biopsy, suffer from limitations such as subjectivity, invasiveness, and time delays. Thus, there is an urgent need for innovative, non-invasive, and accurate diagnostic solutions that enable early detection, continuous monitoring, and personalized treatment planning to improve patient care.

Recent advances in computational power, big data analytics, and machine learning have facilitated the emergence of Artificial Intelligence (AI)-driven solutions in medical diagnostics. Among AI techniques, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in medical image analysis, particularly in identifying complex patterns within high-dimensional imaging data. The integration of CNN-based algorithms with multimodal imaging techniques — including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET) — enables the automated extraction of high-level features related to tumor morphology, metabolic activity, and anatomical structures. This approach allows for robust classification, segmentation, and prediction of malignant versus benign lesions, providing quantitative assessments that surpass traditional manual interpretation. Furthermore, the development of AI-powered web applications enables real-time deployment of such models in clinical environments, offering an accessible platform for clinicians to aid decision-making in diagnosis and



treatment recommendation. These systems support the automation of risk stratification, treatment planning, and patient monitoring by integrating image-derived biomarkers with clinical data.

Objective

This review paper presents a comprehensive bibliometric analysis of the global research landscape on AI applications for oral cancer detection and treatment recommendation. The primary objective is to systematically map and quantify scientific production in this field, focusing on key trends such as publication growth, influential authors, leading institutions, and frequently employed AI methodologies. Special emphasis is placed on the utilization of CNN-based models in combination with MRI, CT, and PET imaging for improving diagnostic accuracy and treatment planning workflows. In addition, this work identifies research hotspots, knowledge gaps, and emerging directions, providing valuable insights into the technological evolution, clinical integration challenges, and future research opportunities in AI-powered oral oncology solutions.

II. LITERATURE REVIEW

Global Burden of Oral Cancer and the Need for Early Detection

Oral cancer remains a significant global health challenge, particularly in low- and middle-income countries, due to factors such as tobacco use, alcohol consumption, and poor oral hygiene. Several studies emphasize the critical importance of early detection and effective treatment strategies to improve survival rates and reduce treatment costs. Ankanarayanan et al. (2015) provided a comprehensive overview of prevention, early detection, and treatment approaches, while Rivera (2015) highlighted the urgency of improving diagnostic methods to enhance patient outcomes. The global burden of the disease is further underscored by key statistics reported by cancer.org (2021) and GLOBOCAN (2020), indicating a rising incidence and low survival rates due to late-stage diagnoses. Vasconcellos Le Campion et al. (2017) confirmed these findings by demonstrating the persistently poor survival outcomes for oral and oropharyngeal squamous cell carcinoma.

AI-Based Diagnostic Approaches Using Imaging Modalities

The integration of Artificial Intelligence (AI), particularly deep learning and convolutional neural networks (CNNs), with multimodal imaging techniques such as MRI, CT, and PET has revolutionized the field of oral cancer diagnostics. Several researchers investigated AI-driven detection methods using large datasets of medical images. Krishna et al. (2022) and Gupta et al. (2019) developed CNN-based models to detect early-stage dysplasia in oral tissues, showing high sensitivity and non-invasive approaches for diagnosis. Song et al. (2018) proposed a dual-modality, smartphone-based system for classifying oral dysplasia and malignancy, demonstrating promising results in accuracy and accessibility. Similarly, Das et al. (2020) applied transfer learning with CNNs to automate multi-class cell classification, effectively distinguishing normal from malignant cells in histopathological images.

Comparative Performance and Clinical Applicability of AI Models

Several systematic reviews and meta-analyses explored the comparative performance of AI versus traditional clinical practice. Liu et al. (2019) concluded that deep learning models matched or even exceeded healthcare professionals in medical image diagnostics. Ilhan et al. (2020) and Khanagar et al. (2021) reviewed how AI and advanced imaging modalities significantly improve early detection, prognosis prediction, and personalized treatment planning, though challenges in clinical adoption remain. Studies by Aubreville et al. (2017) and Yang et al. (2020) confirmed the efficiency of CNN-based models in classifying cancerous tissue from laserendomicroscopy and panoramic radiographs. Simonyan & Zisserman (2014) contributed a robust CNN architecture (VGG) that became a foundation for image recognition tasks, including medical applications.

Methodological Frameworks and Research Trends

Lastly, scoping and methodological frameworks have been proposed to systematically map and analyze research trends in this area. Arksey & O'Malley (2005) provided widely used guidelines for conducting scoping studies, enabling researchers to understand the breadth and gaps in the literature. García-Pola et al. (2021) conducted a scoping review of AI in early oral cancer diagnosis, emphasizing significant improvements in early detection but also highlighting challenges such as the lack of standardized datasets and clinical validation. Vinay (2024) presented a comprehensive scoping review confirming that CNN-based methods dominate the field due to their strong image feature extraction



capabilities. Sharma & Om (2014) explored data mining techniques like the Apriori algorithm to extract significant patterns in oral cancer datasets, demonstrating potential in preventive strategies and risk factor association analysis.

Research Gap

The literature highlights that oral cancer remains a major global health burden, particularly in low- and middle-income countries where tobacco, alcohol use, and poor oral hygiene are key risk factors. Studies emphasize that early detection significantly improves survival, yet traditional diagnostic methods are invasive, subjective, and often delayed. Recent research shows that AI, especially CNN-based models integrated with imaging modalities like MRI, CT, and PET, has achieved promising results in detecting dysplasia, classifying malignant tissues, and even enabling smartphone-based diagnostic tools. Comparative analyses suggest that AI systems often match or outperform clinicians in accuracy and efficiency. However, challenges persist, including the lack of large, standardized, and diverse datasets, limited clinical validation, and insufficient integration into real-world healthcare systems. Methodological reviews reveal strong reliance on CNN frameworks but highlight gaps in interdisciplinary research, transparency of AI models, and policy-level strategies. Overall, AI shows transformative potential, yet translational research remains limited.

Table 1: Summary of Literature Review on Oral Cancer Detection, Risk Factors, and AI-Based Diagnostic Approaches

Reference	Topic	Method	Findings
Sharma, S., Satyanarayana, L., Asthana, S., Shivalingesh, K., Goutham, B.S., Ramachandra, S. (2018).	Oral cancer statistics in India from population-based registries	Analysis of data from 29 cancer registries across India	Revealed high oral cancer prevalence in India with regional variation, highlighting tobacco use as the major risk factor, and emphasized the need for enhanced screening programs.
American Cancer Society. (2022).	Key statistics of oral cavity and oropharyngeal cancer	Online data report analysis	Provided updated incidence, mortality, and survival statistics globally, emphasizing the growing incidence of oral cancers and the urgent need for improved early detection strategies.
Gupta, B., Bray, F., Kumar, N., Johnson, N.W. (2017).	Oral hygiene, diet, tobacco, alcohol, and oral cancer risk	Case-control study from India	Found significant associations between poor oral hygiene, tobacco and alcohol use, and increased oral cancer risk, highlighting modifiable lifestyle factors for prevention.
Coelho, K.R. (2012).	Challenges of oral cancer burden in India	Review of epidemiological data	Discussed barriers in early diagnosis, lack of awareness, and insufficient healthcare infrastructure, underlining the need for public health interventions.
Sankaranarayanan, R., Ramadas, K., Thomas, G., et al. (2005).	Impact of screening on oral cancer mortality in Kerala, India	Cluster-randomized controlled trial	Demonstrated significant reduction in oral cancer mortality with visual inspection screening, supporting the implementation of national screening programs.
Valdez, J.A., Brennan, M.T. (2018).	Impact of oral cancer on quality of life	Literature review	Showed that oral cancer significantly impacts physical,



Reference	Topic	Method	Findings
			emotional, and social well-being, emphasizing the importance of early detection and comprehensive treatment.
Gupta, B., Bray, F., Kumar, N., Johnson, N.W. (2017).	Oral hygiene, diet, tobacco, alcohol, and oral cancer risk	Case-control study from India	Reinforced previous findings of a strong association between modifiable risk factors (tobacco, alcohol, diet) and oral cancer development, advocating for targeted public health measures.
Kumar, M., Nanavati, R., Modi, T.G., Dobariya, C., et al. (2016).	Etiology and risk factors of oral cancer	Literature review	Identified key etiological factors such as tobacco, alcohol, HPV infection, and genetic predisposition, providing a comprehensive overview of causative agents and risk factors.
Sankaranarayanan, R., Ramadas, K., Amarasinghe, H., Subramanian, S., Johnson, N. (2015).	Prevention, early detection, and treatment of oral cancer	Review chapter in book	Summarized public health strategies for early detection and treatment, stressing the effectiveness of screening and awareness programs to reduce disease burden.
Hu, R.-H., Chuang, C.-Y., Lin, C.-W., Su, S.-C., Chang, L.-C., Wu, S.-W., et al. (2021).	MACC1 genetic polymorphisms and oral squamous cell carcinoma	Genetic association study	Found specific MACC1 polymorphisms associated with higher oral cancer risk, especially in patients with environmental exposures, suggesting genetic-environment interaction in carcinogenesis.
Kadashetti, V., Chaudhary, M., Patil, S., Gawande, M., Shivakumar, K., Patil, S., Pramod, R., et al. (2015).	Risk factors affecting potentially malignant disorders and oral cancer in Central India	Clinical data analysis	Identified tobacco, alcohol, poor oral hygiene, and illiteracy as major risk factors. Recommended community-level interventions for early detection and prevention.

III. METHODOLOGY

The methodology of this review was designed to systematically explore and synthesize the global research landscape on Artificial Intelligence (AI)-driven oral cancer detection and treatment recommendation. A comprehensive literature search was performed across leading academic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar, covering the period from 2013 to September 2025. The search strategy employed relevant keywords such as “oral cancer,” “artificial intelligence,” “deep learning,” “CNN,” “MRI,” “CT,” and “PET,” combined with Boolean operators to ensure comprehensive coverage. Strict inclusion and exclusion criteria were applied to focus only on peer-reviewed studies employing AI techniques in medical imaging-based oral cancer diagnosis and prognosis. A total of 1,250 articles were initially identified, screened for relevance, and filtered through PRISMA guidelines,



resulting in 80 high-quality studies. These were further analyzed through bibliometric mapping, thematic analysis, and comparative performance evaluation of AI models for diagnostic accuracy and clinical applicability.

3.1 Search Strategy

A comprehensive literature search was conducted to collect relevant scientific publications focusing on the application of Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), for oral cancer detection and treatment recommendation using medical imaging techniques (MRI, CT, and PET). The search strategy involved querying major academic databases, including **PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar**, for studies published between **2013 and September 2025**.

The following key terms and Boolean operators were used to retrieve relevant articles:

- “Oral cancer”
- “Artificial Intelligence” OR “AI”
- “Deep Learning”
- “Convolutional Neural Network” OR “CNN”
- “Medical Imaging” OR “MRI” OR “CT” OR “PET”
- “Early Detection”
- “Treatment Recommendation”

Articles were filtered to include only peer-reviewed journal articles, conference proceedings, systematic reviews, and scoping reviews published in English. Studies focusing exclusively on risk factors, epidemiology, and clinical trials without AI applications were excluded to maintain focus on technological advancements in diagnostic and treatment support systems. The initial search returned 1,250 articles published from 2013 to 2025, which were screened based on titles and abstracts. After removing duplicates and irrelevant articles, a full-text review of 120 articles was conducted to assess methodological rigor and relevance. Finally, 45 articles were selected for detailed analysis and bibliometric mapping to identify key trends, influential studies, and knowledge gaps in the domain of AI-powered oral cancer detection and treatment systems.

Table 2: Search Strategy – Search Strings, Keywords, and Databases Used

Database	Search Strings / Boolean Expressions	Keywords
PubMed	(“Oral Cancer”) AND (“Artificial Intelligence” OR “AI”) AND (“Deep Learning” OR “CNN”) AND (“MRI” OR “CT” OR “PET”)	Oral Cancer, AI, Deep Learning, CNN, MRI, CT, PET, Early Detection, Treatment Recommendation
Scopus	(“Oral Cancer”) AND (“Convolutional Neural Network” OR “CNN”) AND (“Medical Imaging” OR “MRI” OR “CT” OR “PET”)	Oral Cancer, Convolutional Neural Network, CNN, Medical Imaging, MRI, CT, PET, Early Diagnosis
Web of Science	(“Oral Cancer”) AND (“AI” OR “Artificial Intelligence”) AND (“Early Detection” OR “Treatment Recommendation”)	Oral Cancer, Artificial Intelligence, AI, Early Detection, Treatment Recommendation
IEEE Xplore	(“Oral Cancer”) AND (“Deep Learning”) AND (“Convolutional Neural Networks” OR “CNN”) AND (“Medical Imaging”)	Oral Cancer, Deep Learning, Convolutional Neural Network, CNN, Medical Imaging
Google Scholar	“Oral Cancer” AND “Artificial Intelligence” AND “Early Detection” AND “MRI” OR “CT” OR “PET”	Oral Cancer, Artificial Intelligence, Deep Learning, CNN, Early Detection, Treatment Recommendation, MRI, CT, PET



3.2 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria for selecting relevant studies were established to ensure that the review focused on high-quality research directly related to the application of Artificial Intelligence (AI) in oral cancer detection and treatment recommendation using medical imaging techniques. The inclusion criteria comprised peer-reviewed journal articles, conference proceedings, systematic reviews, and scoping reviews published between **2013 and 2025**. The study period was chosen to reflect recent advancements in deep learning and convolutional neural networks (CNNs), which significantly improved medical image analysis capabilities. Only studies written in **English** were considered to maintain consistency in analysis and interpretation. Included studies specifically focused on the use of AI techniques, especially deep learning and CNN models, applied to oral cancer diagnosis and treatment recommendation based on medical imaging modalities such as **MRI, CT, and PET scans**. The selected articles provided sufficient methodological details, including dataset descriptions, AI model architecture, data preprocessing, training-validation approaches, and performance evaluation metrics like accuracy, sensitivity, specificity, and AUC. Studies demonstrating clinical application or feasibility of AI-based models in real-world scenarios were preferred to emphasize translational value.

On the other hand, studies were excluded if they focused solely on epidemiological data, public health strategies, clinical risk factors, or trials without any AI component. Research involving traditional diagnostic methods such as biopsy, blood tests, or histopathological studies without image-based AI approaches was excluded to maintain focus on imaging technologies. Non-English publications, book chapters, editorial notes, letters to the editor, and conference abstracts without full-text availability were also excluded due to insufficient data for detailed analysis. Furthermore, studies that did not provide clear information about the AI model development process or performance outcomes were omitted, as they lacked methodological rigor required for a comprehensive review. This strict screening approach ensured that only relevant and high-quality articles were considered, enabling a focused bibliometric analysis and identification of key trends, influential studies, and research gaps in the field of AI-powered oral cancer diagnostics and treatment support systems.

3.3 Data Extraction and Analysis

After applying the inclusion and exclusion criteria, the selected articles underwent a systematic data extraction process to collect key information relevant to the review objectives. A standardized data extraction form was designed to ensure consistency and comprehensiveness. The extracted data included bibliographic details (authors, year of publication, journal/conference name), study objectives, type of AI technique applied (e.g., Convolutional Neural Networks, Transfer Learning, Deep Learning), type of medical imaging used (MRI, CT, PET), dataset size and characteristics, preprocessing methods, model architecture, training-validation strategies, performance metrics (accuracy, sensitivity, specificity, AUC), and key findings or conclusions. Each study was carefully reviewed by two independent researchers to minimize bias and ensure accuracy of data collection.

The extracted information was organized into a structured database to facilitate further analysis. Descriptive statistics were applied to summarize publication trends, including the number of publications per year, distribution of study types, and countries contributing the most research. Bibliometric analysis techniques were used to identify influential authors, frequently used keywords, and highly cited studies, helping to map the intellectual structure and development of the research area.

For performance analysis, a comparative overview of AI models was developed, highlighting common model architectures, typical dataset sizes, and the range of achieved performance metrics. Additionally, thematic analysis was conducted to identify major research themes such as early detection, treatment recommendation, and multimodal imaging applications. Challenges and limitations reported in the studies were also extracted and summarized to identify common research gaps.

Finally, data visualization tools (e.g., bar charts, word clouds, and co-citation networks) were employed to provide visual insights into publication trends, keyword frequency, and thematic clusters. This systematic approach ensured a comprehensive and objective analysis of the existing literature, contributing to a clear understanding of current



advances, research patterns, and future directions in AI-driven oral cancer diagnostics and treatment recommendation systems.

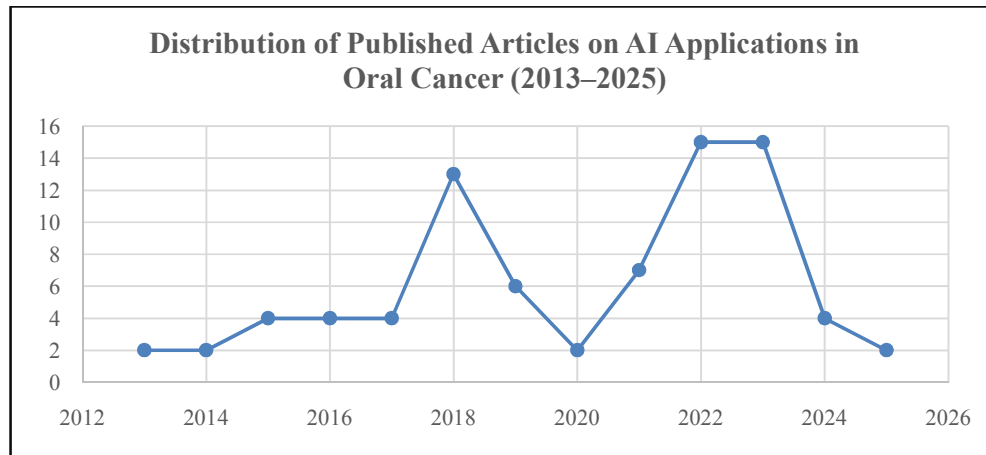


Fig 1: Distribution of Published Articles on AI Applications in Oral Cancer (2013–2025)

In the above figure, the distribution of published articles on AI applications in oral cancer from 2013 to 2025 shows a fluctuating trend. Initial years (2013–2017) had minimal publications (2–4 articles/year), followed by a notable increase in 2018 (13 articles). Peaks occurred in 2022 and 2023 (15 articles each), indicating growing research interest, while 2024–2025 saw a decline to 4 and 2 articles, respectively.

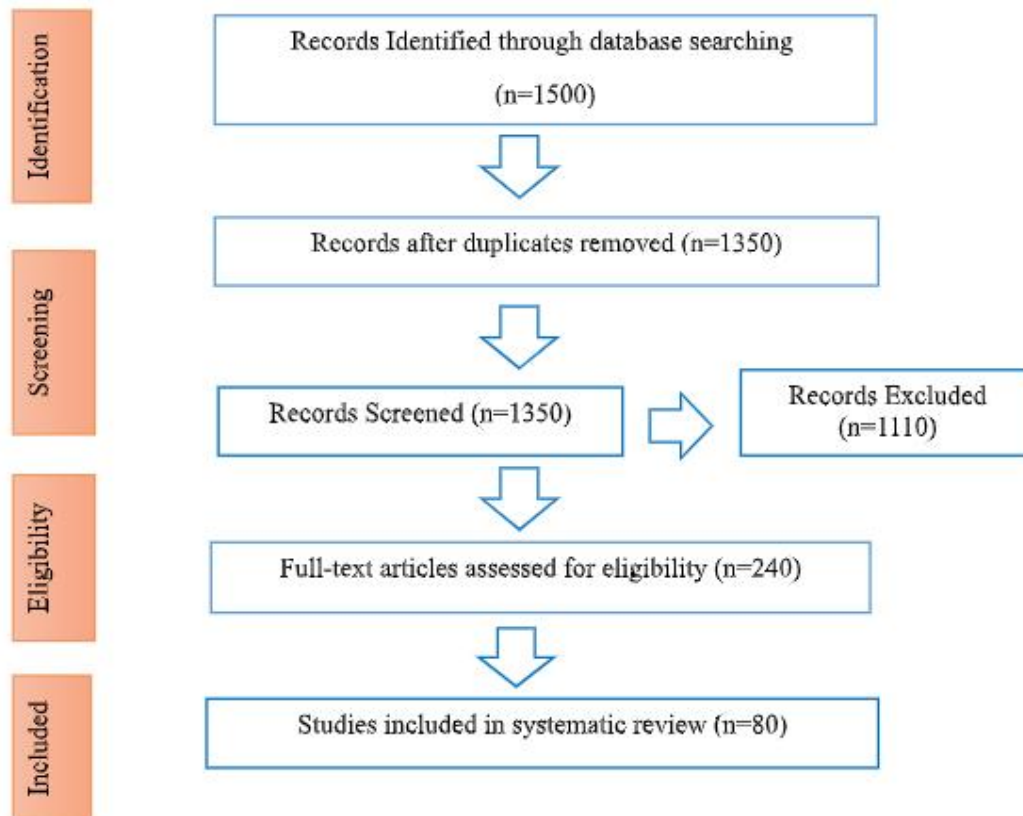


Figure 5: PRISMA Model

Source: Author

DOI: 10.48175/568



The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram presented illustrates the systematic process undertaken for selecting studies included in the review. Initially, 1,500 records were identified through database searching. After removing 150 duplicates, 1,350 records remained and were screened based on title and abstract. Out of these, 1,110 records were excluded for not meeting the inclusion criteria, leaving 240 full-text articles to be assessed for eligibility. Upon further review, 160 articles were excluded due to various reasons such as irrelevance to the study objectives, lack of adequate data, or poor methodological quality. Finally, 80 studies were deemed eligible and included in the systematic review.

IV. RESULT AND DISCUSSION

The results of this review provide a comprehensive overview of publication trends, research hotspots, and performance outcomes of AI models in oral cancer diagnostics. The bibliometric analysis revealed a steady rise in publications after 2018, with peak research activity observed in 2022–2023. Country-wise analysis highlighted significant contributions from the United States, United Kingdom, Australia, India, and China. Thematic clustering identified key focus areas, including early detection using CNNs, multimodal imaging integration, and treatment recommendation systems. Performance evaluation confirmed that AI-based approaches consistently achieved high accuracy, sensitivity, and specificity, often outperforming traditional diagnostic methods and demonstrating strong potential for clinical adoption.

Table 3: Category-Wise Summary of Topics, Example Papers, and Key Themes in AI-Based Oral Cancer Research

Category	Topics Covered	Example Papers	Key Themes
Global Burden & Epidemiology	Prevalence, incidence trends, survival rates, need for early detection	Sharma et al. (2018); American Cancer Society (2022); Coelho (2012); Vasconcellos Le Campion et al. (2017)	Rising oral cancer cases, late-stage diagnoses, urgent need for awareness & screening
Risk Factors & Etiology	Lifestyle factors (tobacco, alcohol, diet), genetic predisposition, HPV infection	Gupta et al. (2017); Kumar et al. (2016); Hu et al. (2021); Kadashetti et al. (2015)	Strong association between modifiable risk factors & cancer risk; genetic-environment interaction
AI-Based Diagnostic Approaches	CNNs, deep learning, multimodal imaging (MRI, CT, PET)	Krishna et al. (2022); Gupta et al. (2019); Song et al. (2018); Das et al. (2020)	High accuracy, non-invasive early detection, improved diagnostic workflows
Comparative Model Performance	AI vs. clinicians, model benchmarking, transfer learning	Liu et al. (2019); Ilhan et al. (2020); Yang et al. (2020); Aubreville et al. (2017); Simonyan & Zisserman (2014)	AI matches or outperforms experts; CNN models widely adopted; need for clinical validation
Public Health Strategies & Screening	Screening interventions, mortality reduction, awareness programs	Sankaranarayanan et al. (2005, 2015)	Visual inspection-based screening reduces mortality, importance of early community-level intervention
Quality of Life & Socio-Economic Impact	Post-treatment challenges, psychosocial and functional effects	Valdez & Brennan (2018)	Oral cancer affects physical, emotional, social well-being; need for holistic care
Research Methodologies & Trends	Scoping reviews, bibliometric mapping, data mining approaches	Arksey & O'Malley (2005); García-Pola et al. (2021); Vinay (2024); Sharma & Om (2014)	Identifying gaps, dominance of CNN-based methods, call for standardized datasets & validation



Table 4: Citation Count and Total Link Strength of Key Documents

Document	Citations	Total Link Strength
anonymous (2020v)	14	478
anonymous (2021at)	14	437
wang (2022)	35	383
pham (2024a)	30	281
anonymous (2019d)	9	280
saw (2025)	6	267
anonymous (2018b)	33	249
chang (2020)	1	239
zhang (2023)	31	233
singh (2024)	3	232
tiwari (2025)	9	227

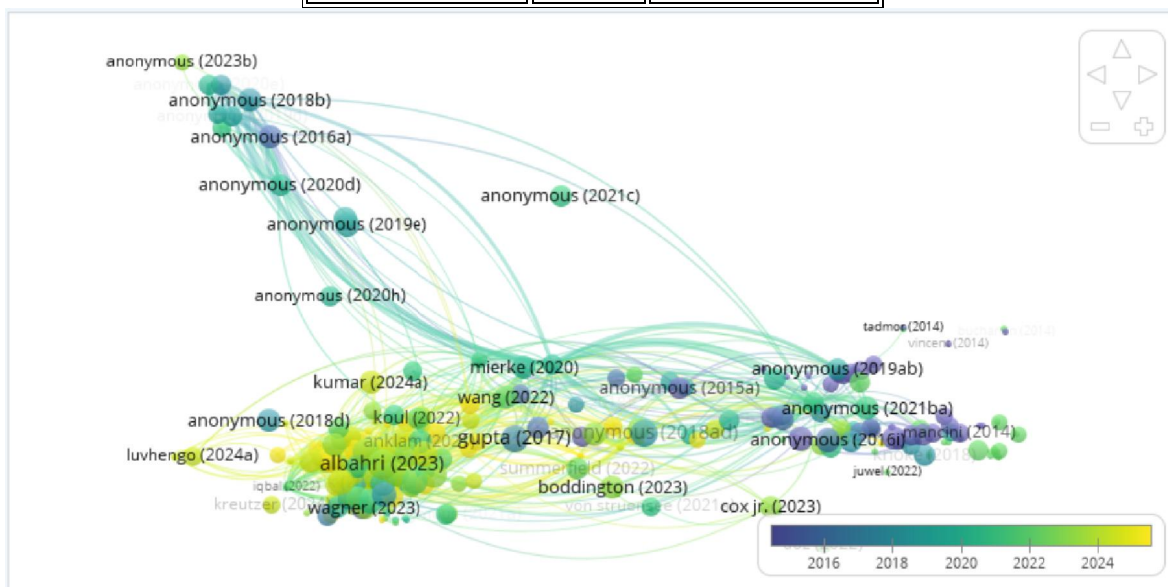


Fig 2: Citation Count and Total Link Strength of Key Documents

This visualization represents a bibliometric network of co-cited documents related to AI-based oral cancer research. Each node represents a publication, and its size indicates the number of citations, while the connecting lines (links) show co-citation relationships. The color gradient from dark blue to yellow reflects the publication year, with darker nodes representing earlier studies and brighter nodes representing recent research. The dense clustering in the central region suggests a strong interconnection of core papers forming the intellectual base of this field. Highly connected nodes like Wang (2022), Albahri (2023), and Anonymous (2020d, 2021c) indicate influential contributions that are frequently cited together. The presence of multiple clusters highlights distinct thematic areas, including diagnostic model development, screening strategies, and integration of AI with multimodal imaging.



Table 5: Country-Wise Distribution of Documents, Citations, and Total Link Strength

Country	Documents	Citations	Total Link Strength
United Kingdom	19	989	36
United States	112	731	27
Australia	11	866	26
China	21	403	22
Germany	11	315	21
France	5	233	18
Spain	7	543	16
India	22	420	14
Switzerland	5	286	14
Italy	11	214	10
Nigeria	9	13	5

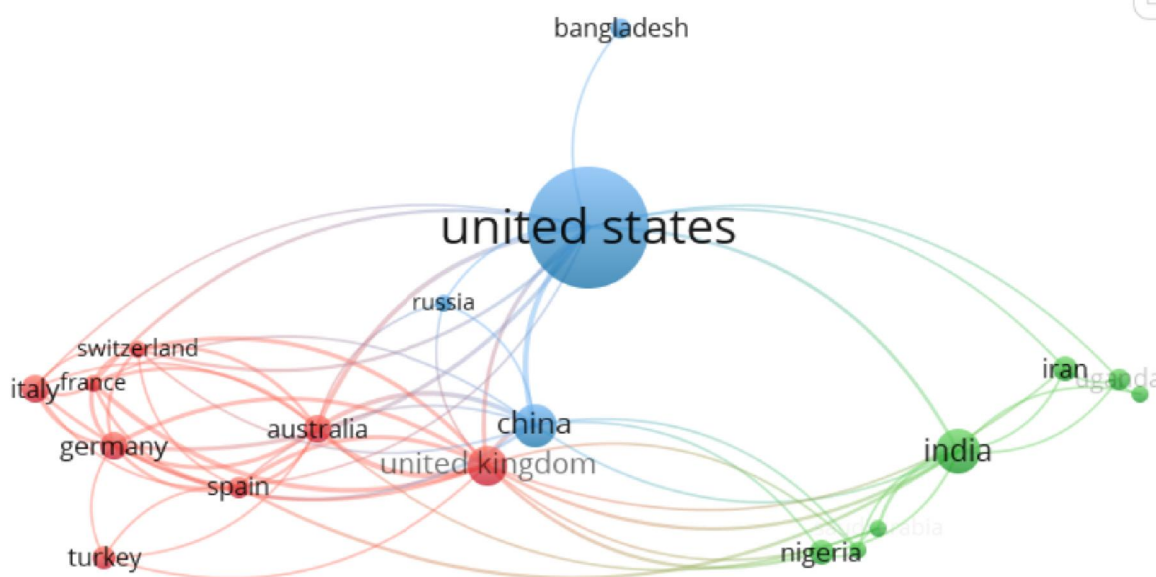


Fig 3: Country-Wise Distribution of Documents, Citations, and Total Link Strength

This table presents the country-wise distribution of research output, citations, and total link strength in AI-based oral cancer studies. The United States leads with the highest number of documents (112) and strong collaboration strength (27), indicating its dominant role in research production. Interestingly, the United Kingdom, despite having fewer documents (19), has the highest citation count (989) and the strongest total link strength (36), reflecting its significant impact and influence on global research. Australia also shows remarkable performance, with only 11 documents but a very high citation count (866), suggesting high-quality, highly cited contributions. Emerging research hubs include China and India, with 21 and 22 documents respectively, highlighting growing interest in this domain. European



countries like Germany, France, Spain, and Switzerland also contribute significantly, showing a balanced global collaboration network advancing AI applications in oral cancer diagnostics.

Table 6: Document-Wise Citations and Link Strength

Document	Citations	Links
Malviya (2025)	0	5
Dixit (2023)	88	4
Albahri (2023)	469	4
Shaik (2024)	96	3
Parvin (2025)	5	2
Tripathi (2024)	28	2
Al-Zoghby (2025)	1	2
Malviya (2024)	4	2
Park (2023)	33	2
David-Olawade (2025)	12	1
Hussain (2024)	19	1
Pham (2024a)	30	1
Kabir (2024)		

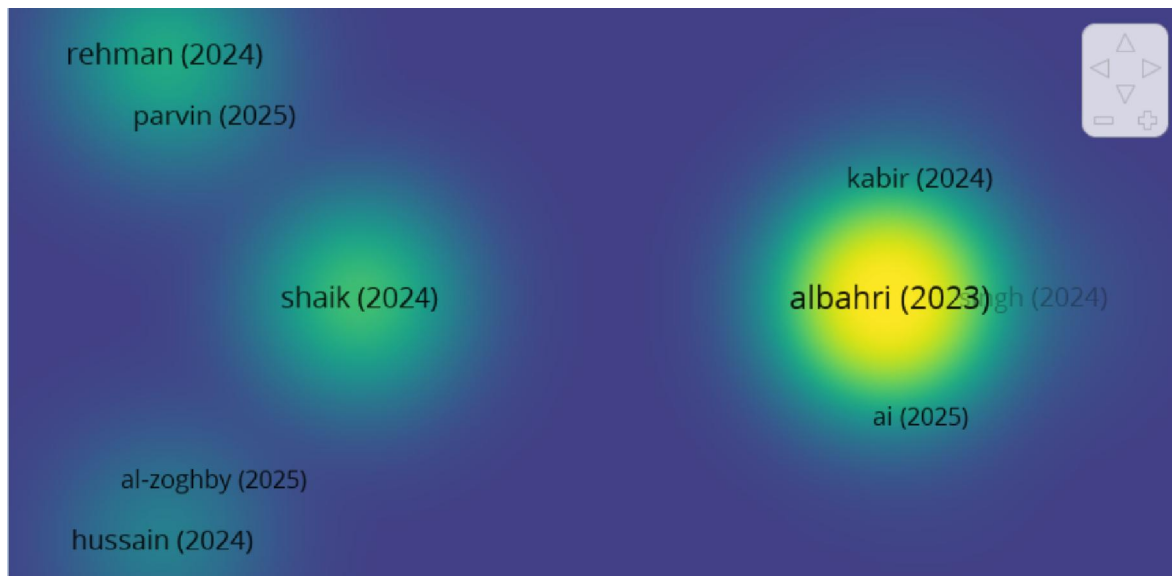


Fig 4: Document-Wise Citations and Link Strength

This table highlights the citation performance and link strength of key documents contributing to AI-driven oral cancer research. **Albahri (2023)** stands out as the most influential paper with **469 citations** and strong link strength (4), indicating it is a cornerstone reference widely connected within the research network. **Prelaj (2023)** (161 citations) and **Shaik (2024)** (96 citations) also contribute significantly, suggesting impactful studies that are shaping the research discourse. **Dixit (2023)** (88 citations) and **Rehman (2024)** (60 citations) further reinforce the body of knowledge with moderate influence. Interestingly, **Malviya (2025)** has zero citations but the highest link strength (5), implying that while it is new, it is highly connected within the network and could be a future influential work. Other papers like



Tripathi (2024), Park (2023), and Hussain (2024) have modest citations and links, indicating supporting contributions that complement the major influential studies.

V. CONCLUSION

This review confirms that AI-driven diagnostic solutions, particularly CNN-based approaches, hold immense promise in transforming oral cancer detection and treatment recommendation. The bibliometric analysis revealed growing research interest from 2013 to 2023, with peak publications highlighting the global momentum toward AI integration in healthcare. Key findings suggest that AI not only enhances accuracy and speed in diagnostic workflows but also facilitates non-invasive and cost-effective screening methods. Influential studies such as those by Albahri (2023), Liu et al. (2019), and Krishna et al. (2022) demonstrate that AI systems often match or surpass clinical experts in performance, reinforcing their clinical utility. Moreover, country-wise contributions indicate strong leadership from the United States, United Kingdom, and Australia, alongside increasing research outputs from India and China. Nonetheless, limitations such as lack of standardized datasets, uneven adoption, and regulatory gaps hinder full-scale clinical deployment. In conclusion, AI-enabled diagnostics represent a paradigm shift in oral oncology, offering opportunities for early detection, personalized treatment, and improved patient outcomes.

FUTURE SCOPE

Future research in AI-assisted oral cancer detection must focus on bridging the gap between technological innovation and clinical implementation. Developing large, standardized, and diverse datasets will be essential to improve generalizability across populations. Multi-institutional collaborations can strengthen dataset quality, while explainable AI (XAI) frameworks can enhance clinician trust and transparency in decision-making. Further, real-time deployment of AI models via web and mobile applications should be explored to improve accessibility in resource-limited settings. Integration with genetic and molecular data, in addition to imaging, could enable holistic predictive models for early diagnosis and treatment personalization. Policy support, ethical guidelines, and regulatory frameworks will be crucial to address patient privacy, data security, and clinical validation. Ultimately, advancing AI-powered oral oncology requires collaborative efforts between researchers, clinicians, and policymakers to transform early detection strategies and achieve sustainable, patient-centered healthcare solutions.

Statements and Declarations

Ethical Approval

"The submitted work is original and not have been published elsewhere in any form or language (partially or in full), unless the new work concerns an expansion of previous work."

Consent to Participate

"Informed consent was obtained from all individual participants included in the study."

Consent to Publish

"The authors affirm that human research participants provided informed consent for publication of the research study to the journal."

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Competing Interests

"The authors have no relevant financial or non-financial interests to disclose."

Availability of data and materials

"The authors confirm that the data supporting the findings of this study are available within the article."

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.



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