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Systematic Review

Beyond traditional methods-artificial intelligence in detection of oral cancer using smartphone-based oral photographs: a systematic review

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ABSTRACT

Oral cancer is a significant global health concern that affects people of various age groups worldwide. According to Globo Can, reports from 2022 show that approximately 377,713 new cases and 177,757 deaths are reported each year worldwide. Smartphones and Artificial intelligence (AI) are increasing in healthcare for diagnosis and treatment planning. This systematic review aims to appraise the existing evidence on the effectiveness of various artificial intelligence algorithms in the detection of oral cancer based on smartphone-based oral photographs from previously published articles. A systematic electronic search was carried out through various databases that emphasize current studies on the detection or diagnosis of oral cancer using different artificial intelligence algorithms. A modified Newcastle Ottawa scale was used to evaluate the quality of the included research and the PROBAST (Prediction model Risk of Bias Assessment tool) was used to assess the risk of bias. Among 13 articles, 8 show good quality and 5 fair qualities, mostly at low bias risk. Machine learning (support vector machines) sensitivity and specificity range from 89% to 92% and 75% to 82%; deep learning (MobileNet v2, ResNet) ranges from 85.12% to 90.23% and 87.64% to 90%. The diagnostic effectiveness of artificial intelligence models differs among machine learning and deep learning techniques. According to these results, machine learning has demonstrated encouraging outcomes in identifying oral cancer. The findings demonstrate the effectiveness of smartphone photographic images in detecting oral cancer.

Keywords: Artificial intelligence, Deep learning, Machine learning, Mobile phones, Mobile-based images, Oral cancer detection

INTRODUCTION

Oral cancer is a major concern worldwide in terms of public health that affects people of various age groups, mostly the middle-aged, irrespective of gender. According to Globo Can, reports in 2022 show that approximately every year, there are reports of 377,713 new cases and 177,757 deaths globally.[1] In the Indian subcontinent, since it ranks as one of the top three cancer types, oral cancer is an important threat to public health.[2] Between 2018 and 2020, there was a 12% rise in new cases, going from 119,992 to 135,929, as reported by Globo Can in 2018 and 2020.[3] Because there are few specialists and medical facilities in low and middle income countries, screening programs need to offer a cost-effective diagnosis method. Oral cancer and other potentially malignant disorders (OPMDs) are on the rise in low- and middle-income countries. Scarce resources in remote regions lead to delayed detection of these abnormalities in the population, causing higher mortality rates and reducing the quality of life. Early detection of oral cancer lesions can enhance patient outcomes and overall quality of life. An oral examination by a dental professional is the foundational method to identify oral abnormalities.[4]

Recently, the introduction of artificial intelligence (AI) has marked the beginning of a new era in medical diagnostics, offering to surpass the constraints of conventional approaches. AI, specifically machine learning (ML) and deep learning (DL) algorithms, have shown impressive abilities in accurately and quickly analyzing large volumes of data. AI is used in healthcare for precise cancer detection, early identification of deadly blood diseases, virtual health aids, streamlining healthcare tasks, organizing medical records, robot-assisted surgeries, automated image analysis and enhanced healthcare availability. Convolutional neural networks (CNNs) are a valuable tool for addressing image classification issues and have been extensively utilized in various medical image analysis tasks due to their impressive performance. Deep convolutional neural networks have the potential to automatically classify various types of cancer lesions, like skin, cervical and oral cancer. Clinicians can access a user-friendly Android app for real-time classification results in low-resource settings, even without the internet. Deep learning displays exceptional effectiveness, indicating that, with further refinement and testing, an AI-powered screening program could be created for settings with minimal resources. AI and digital images have the potential to be used in cancer detection. As smartphones are now commonly used, oral cancer detection through mobile devices provides an affordable screening method that is easily accessible for many people. Due to the quick advancement in imaging and sensing technologies in camera systems, smartphones are now equipped with superior camera modules that offer better quality, less noise and quicker capabilities. The utilization of smartphone-based white light inspection techniques is an effective way to capture images of the mouth. The widespread use of mobile devices and improvements in imaging technology presents a special chance to create teledentistry programs for early identification and referral of oral cancer.[8] There has been a notable rise in clinical studies and articles that assess how effective Artificial Intelligence algorithms are in spotting oral cancer. Therefore, we considered performing a comprehensive review to determine the supporting evidence for employing different AI algorithms (machine learning and deep learning) in detecting oral cancer. This systematic review evaluates the current evidence on how well different artificial intelligence algorithms Machine learning and Deep learning can detect oral cancer using oral photographs taken with smartphones.

Objective

To evaluate how well AI technologies can detect oral cancer early by reviewing and analyzing existing evidence.

METHODS

Protocol and registration

This research protocol follows the guidelines established by the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA). The systematic review protocol was registered on PROSPERO under registration ID 499888.

Research question

What is the efficiency of artificial intelligence in identifying oral cancer from images captured on mobile phones.

Study design and eligibility criteria

A systematic review was conducted based on the research question, which includes the PECO statement

Participants

Articles included photographic images of patients for detecting oral cancer.

Exposure

Artificial intelligence used in mobile phones to detect oral cancer.

Comparison

Not applicable.

Outcome

Effectiveness of oral cancer detection by AI-based mobile application.

Inclusion criteria

Human studies have utilized artificial intelligence in smartphones, such as machine learning and deep learning algorithms, to detect oral cancer. Articles only in the English language were included. Articles focusing on the usage of photographic images for the detection of oral cancer.

Exclusion criteria

Animal studies. Studies in the form of histology. Reviews of literature, individual case studies, brief communications, personal perspectives, editorials and abstracts from conferences.

Systematic reviews, meta-analyses and umbrella reviews were excluded. Studies discussing the potential of AI in treatment planning.

Outcomes

Participants

Articles assessing the mobile-based clinical images of patients with oral cancer using AI technology.

Exposure

Articles assessed the ability of various Artificial Intelligence algorithms to detect, diagnose and predict oral cancer based on the images.

Outcome

Articles that assessed the AI algorithms in detecting oral cancer using mobile-based photographs.

Search strategy

An extensive electronic search was conducted across databases including PubMed, Scopus, Web of Science, EMBASE, Google Scholar, Cochrane database of systematic reviews and Trip database to locate relevant studies. Research conducted from 2017 was considered because of the serious evolution of Artificial intelligence in oral cancer screening and investigations for pertinent studies were carried out until September 2024. In cases where pertinent articles were discovered without complete text, the authors were emailed to obtain the articles. The search query used was derived from the PECO statement. The search utilized the keywords Artificial Intelligence, Oral cancers, machine learning and deep learning on oral photographs acquired from the Medical Subject Headings (MESH terms). The Boolean operators AND and OR are utilized with these keywords. PubMed utilized search strategies such as combining Artificial Intelligence with OPMD, Artificial Intelligence with diagnosis, oral cancer with diagnosis and oral photographs and oral photographs with Artificial Intelligence and further narrowed results by filtering for "only articles". The Cochrane database utilized identical keywords with no additional filters. The search method was employed in PubMed, Cochrane and Embase.

Study selection

The selection process was primarily done by 2 investigators independently. This was accomplished by having each investigator independently review the study's title and abstract. After the article search was done using the keywords and Boolean operators, the individual studies from each database mentioned above were noted down separately. Subsequently, references to those studies and duplicates were managed using the Zotero software. The software mentions duplicate studies and can be easily identified and merged into a single study. The articles and studies that satisfied the minimum eligibility requirements. After the full-text publications were screened for eligibility, duplicates that didn't pertain to the study topic were removed. The PRISMA flowchart provides a detailed overview of the qualifying studies (Figure 1).

Risk of bias and quality of the studies assessment

The PROBAST tool was employed to evaluate bias and relevance in nonrandomized studies. PROBAST consists of 20 questions spanning across 4 distinct categories: participants, predictors, outcomes and analysis. Affirmative, likely affirmative, negative, negative or no data was given in answer to each query. For a domain to be classified as low risk, all questions should have been answered with either yes or likely yes. If any question in a specific area received a negative or likely negative answer, the research was considered to have a high risk of bias unless the evaluators concluded that the risk was low or unsure after considering all the indicators. Likewise, for a study to be classified as having an uncertain risk, at least one area must be assessed as having an uncertain bias, while the remaining areas must be evaluated as having a minimal bias.

Data collection

The initial searches were carried out on Pub Med, Scopus, Web of Science, EMBASE, Google Scholar, Cochrane database of systematic reviews and Trip database in order to locate relevant studies. A total of 114 studies were included. Out of these results, a certain number of reviews were removed because they were duplicated and (n=57) were omitted after reviewing the abstract and title, as they were considered irrelevant and excluded records (n = 7). Histological studies (n=16), literature reviews and case reports (n=10), systematic reviews (n=04) and studies on the role of AI in treatment planning (n=4) led to the omission of complete articles; two reviewers collected the primary data. The data was later verified to ensure correctness. The authors gathered key information from articles, such as authors, publication year, research objectives, databases searched, number of studies included, bias assessment tools, results and conclusions.

Assessment of methodological quality

The quality assessment used a revised Newcastle Ottawa scale for cross-sectional studies, with higher scores indicating better study quality. Research studies scoring between 6-9 are classified as good quality, while those scoring between 3-6 are seen as fair quality and those scoring between 0-2 are considered poor quality. The review consists of 8 high-quality studies and 5 fair-quality ones that were assessed for quality, is shown in (Table 3).

RESULTS

The articles analyzed in the systematic review showed how Artificial Intelligence can effectively diagnose oral cancer in oral photographs taken with mobile phones. A database search initially identified 114 records, with an additional 8 records found through other sources. 13 out of 57 reviewed articles were selected for analysis. The PRISMA flowchart (Figure 1) provides a thorough explanation of the systematic reviews that have been included.

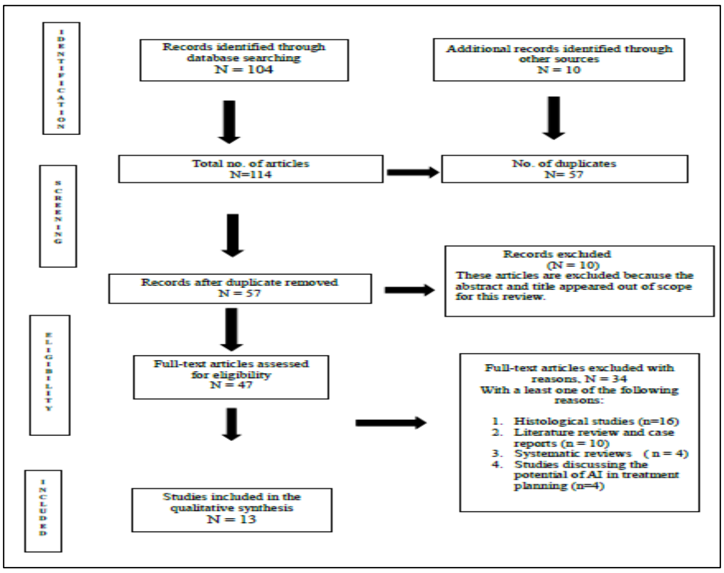

Figure 1: PRISMA flow diagram showing the identified article.

The PROBAST tool was utilized for conducting risk assessment. Out of the 13 studies analyzed, 9 had a low risk of bias, 3 were considered high risk and 1 had an unclear risk of bias. PROBAST consists of 20 questions spanning across 4 distinct domains: participants, predictors, outcomes and analysis. Yes, most likely yes, a negative or unspecified response was given for each inquiry. For a domain to be deemed low risk, all questions must have been answered with either yes or most likely yes. If any question in a domain received a negative or likely negative response, the study was deemed to have a high risk of bias unless assessors deemed the risk to be low or unclear based on overall indicators. Likewise, for a study to be deemed as having an unclear risk, one domain must be assessed as having an unclear bias risk, while the rest of the domains must be rated as low risk. This assessment was conducted for all the studies included (Table 2). Based on the studies analysed, this review indicates that machine learning has an average sensitivity and specificity between 89% to 92% and 75% to 82%, while deep learning has an average sensitivity and specificity ranging from 85.12% to 90.23% and 87.64% to 90%.

Table 1: Search strategy employed in various databases.

Database	Search terms	
PubMed	#6	#1 AND #2 AND #3 AND #4 OR # 5
	#5	(“addresses” (Publication Type) OR “biography” (Publication Type) OR “case reports” (Publication Type) OR “comment” (Publication Type) OR “directory” (Publication Type) OR “editorial” (Publication Type) OR “interview” (Publication Type) OR “lectures” (Publication Type) OR “legal cases” (Publication Type) OR “legislation” (Publication Type) OR “letter” (Publication Type) OR “news” (Publication Type) OR “newspaper article” (Publication Type) OR “patient education handout” (Publication Type) OR “popular works” (Publication Type) OR “congresses” (Publication Type) OR “consensus development conference” (Publication Type) OR “consensus development conference, ” (Publication Type) OR “practice guideline” (Publication Type))
	#4	((systematic review (Title/Abstract)) OR (meta-analysis (Title/ Abstract)))
	#3	(((Artificial Intelligence (Title/Abstract)) OR (oral cancer(All Fields))) OR (diagnosis (Title/Abstract))))
	#2	("artificial intelligence"(MeSH Terms) OR ("artificial"(All Fields) AND "intelligence"(All Fields)) OR "artificial intelligence"(All Fields)) AND (("cell phone"(MeSH Terms) OR ("cell"(All Fields) AND "phone"(All Fields)) OR "cell phone"(All Fields) OR ("mobile"(All Fields) AND "phone"(All Fields)) OR "mobile phone"(All Fields)) AND ("based"(All Fields) OR "basing"(All Fields)) AND ("image"(All Fields) OR "image s"(All Fields) OR "imaged"(All Fields) OR "imager"(All Fields) OR "imager s"(All Fields) OR "imagers"(All Fields) OR "images"(All Fields) OR "imaging"(All Fields) OR "imaging s"(All Fields) OR "imagings"(All Fields))) AND ("machine learning"(MeSH Terms) OR ("machine"(All Fields) AND "learning"(All Fields)) OR "machine learning"(All Fields)) AND "deeplearning"(All Fields)
	#1	artificial"(All Fields) AND "intelligence"(All Fields) AND ("mobile"(All Fields) AND "phone"(All Fields) AND "based"(All Fields) AND "images"(All Fields)) AND ("machine"(All Fields) AND "learning"(All Fields)) AND "deep learning"(All Fields) AND ("oral"(All Fields) AND "cancer"(All Fields) AND "detection"(All Fields)) AND ("mobile"(All Fields) AND "phones"(All Fields))
Scopus	#3	Artificial Intelligence machine learning deep learning AND oral cancer detection

Continued.

Database	Search terms	
	#2	Artificial Intelligence AND machine learning AND mobile phones OR oral cancer detection
	#1	Artificial Intelligence AND deep learning AND mobile phones OR oral cancer detection
Web of Science	#2	Artificial Intelligence AND Mobile phones AND deep learning AND mobile phones OR oral cancer detection
	#1	Artificial Intelligence AND machine learning OR deep learning AND mobile phone AND oral cancer detection AND intraoral images
Embase	#2	Artificial Intelligence AND machine learning OR deep learning AND mobile phones AND oral cancer detection
	#1	Artificial Intelligence AND machine learning OR deep learning AND mobile phones AND oral cancer detection AND intraoral images
Cochrane	#4	Artificial Intelligence AND machine learning OR deep learning AND mobile phones AND oral cancer detection
	#3	Artificial Intelligence AND oral cancer AND diagnosis AND intraoral images
	#2	Artificial Intelligence AND oral cancer AND clinical images
	#1	Artificial Intelligence OR neural networks AND oral cancer detection AND intraoral clinical images AND mobile phones.
Trip Database	#3	Artificial Intelligence AND machine learning AND deep learning AND mobile phones AND oral cancer detection AND intraoral images OR photographic images
	#2	Artificial Intelligence OR Neural networks OR AI algorithms AND oral cancer AND diagnosis AND prediction
	#1	Artificial Intelligence OR AI algorithms AND oral cancer AND diagnosis AND intraoral images OR clinical images OR photographs
Google Scholar	#3	Artificial Intelligence OR AI algorithms AND oral cancer AND diagnosis AND intraoral images OR clinical images OR photographs
	#2	Artificial Intelligence AND machine learning AND deep learning AND oral cancer AND cancer detection AND intraoral images OR photographic images
	#1	Artificial Intelligence OR neural networks AND AI algorithms AND oral cancer AND intraoral images AND cancer detection

Table 2: PROBAST tool to assess the risk of bias and applicability.

Authors	Types of study	Risk of bias				Applicability			Overall	
		Participant selection	Predictors	Outcome	Analysis	Participant	Predictors	Outcome	Risk of bias	applicability
Priyathane et al[10]	Development and validation	+	_	+	+	+	_	+	_	_
Dinesh et al[9]	Development and validation	+	_	_	_	+	+	+	+	+
Vivek et al[14]	Development and validation	+	+	+	_	+	+	+	_	_
Emman et al[13]	Development and validation	+	_	_	_	+	_	_	_	+
Praveen et al[20]	Development and validation	+	+	+	+	+	+	+	+	+
Paranasree et al[11]	Validation	+	_	+	_	+	+	_	+	_
Huiping et al[16]	Development	+	+	_	_	+	+	+	+	+
Jubair et al[19]	Development and validation	+	+	?	+	_	+	+	+	+
Bofan et al.[7]	Development and validation	_	+	+	+	+	+	+	+	+
Gonzalez et al[12]	Development and validation	+	+	+	+	_	+	_	_	+
Wellikala et al[18]	Development and validation	+	+	_	+	_	+	+	+	+
Uthoff et al[15]	Development and validation	+	+	+	+	+	+	+	+	+
Wellikala et al[17]	Development and validation	+	_	_	+	+	+	+	_	_

+-Low risk of bias/low concerns regarding applicability, _-high risk-off bias /high-risk concerns regarding applicability, ?-Unclear risk of bias/unclear risk concerns regarding applicability.

Table 3: Results of the quality assessment for included studies using the modified Newcastle Ottawa as scale for cross-sectional studies.

Studies	Selection				Comparability		exposure			Total
	Definition of cases	Representativeness of cases	Selection of control	Definitions of control	On age	Other risk factors	Ascertainment of exposure	The same methods of ascertainment for cases and controls	Non-response rate	
Piyarthane et al[10]	1	1	1	1	0	0	1	1	0	6
Dinesh et al[9]	1	1	0	0	0	0	1	1	0	4
Vivek et al[14]	1	1	1	1	0	0	1	1	0	6
Emman et al[13]	1	1	0	0	0	0	1	1	1	5
Parnasree et al[11]	1	1	0	0	0	0	1	1	0	4
Praveen et al[20]	1	1	1	1	0	0	1	1	1	7
Huiping et al[16]	1	1	1	1	0	0	1	1	0	6
Jubair et al[19]	1	1	1	1	0	0	1	1	0	6
Bofan et al[7]	1	1	1	1	0	0	1	1	0	6
Gonzalez et al[12]	1	1	0	0	0	1	1	1	0	5
Wellikala et al[17]	1	1	1	1	0	0	1	1	0	6
Uthoff et al[15]	1	1	0	0	0	0	1	1	0	4
Welikala et al[18]	1	1	0	1	1	0	1	1	0	6

Table 4: Characteristics of the studies included in the systematic review.

S. no	Author, year, country	Study Design/sample size	ML/DL	Type of cancer	Source of illumination	Statistical findings (AUC, sensitivity, specificity, etc)	Main outcome
1	Piyarathne et al[10] 2024, Srilanka	Cross-sectional N=3000 images	ML	Oral cancer	White light imaging	–	AI(artificial intelligence) and ML(machine learning) using WLI(white light imaging) can enhance patient care via community screening and addressing socioeconomic inequalities in health.
2	Dinesh et al, 2023	Cross-sectional	ML	Oral squamous cell carcinoma	Light-based imaging Chemo fluorescence	Sensitivity-89%, Specificity-75%	Machine learning aids patients and dentists in detecting lesions like OSCC and OPMDs, improving early identification and treatment based on intraoral images.
3	Vivek et al[14], 2022, India	Cross-sectional N= 2178 clinical intra-oral images	DL	Oral cancer	White light imaging	Precision - 86% recall(sensitivity)-85%,specificity – 83%, F1score	This research explores artificial intelligence methods for identifying precancerous abnormalities using images of the oral cavity in India, underscoring the capabilities of deep learning models for

Continued.

S. no	Author, year, country	Study Design/sample size	ML/DL	Type of cancer	Source of illumination	Statistical findings (AUC, sensitivity, specificity, etc)	Main outcome
						_86%,	conducting screenings in resource-constrained regions.
4	Emman et al[13] 2023, Egypt	Cross-sectional N=455	DL	0ral squamous cell carcinoma	White light imaging	Sensitivity-83.0% specificity-96.6% accuracy-84.3% F1score - 83.6%	Taking well-positioned pictures of the mouth improves the effectiveness of deep learning technology in detecting oral cancer, offering the potential for diagnosing with smartphones using pictures.
5	Parnasree et al.[11] 2023, India	Cross sectional N =175 images	DL	Oral cancer	Autofluorescence	Mean Sensitivity - 88.5%, Mean Specificity-89%, Accuracy - 89%	The approach suggests utilizing Autofluorescence imaging with AI algorithms for oral cancer detection and classification, incorporating image features, medical history, age, gender and tobacco use..
6	Praveen et al[20], 2022, India	Cross-sectional N=5025	ML	Oral cancer	-	Sensitivity - 95% Specificity - 84%	The study shows an automated dual-image mHealth system enhances screening for oral cancer in resource-limited settings for healthcare workers. mHealth can be used to provide health education, promote behavior change, facilitate decision support in the diagnosis and management of a wide variety of conditions, support diagnostic testing or link medical records
7	Huiping et-al[16], 2016, China	Cross-sectional N= 760	DL	Oral cancer	-	Sensitivity-83% Specificity-96.6%	Improving the performance of the deep learning algorithm in detecting oral cancer can be achieved by capturing images of the lesion in focus, optimizing the training dataset and utilizing the HRNet. HR-NET provides fine-grained, connection-level fail over across communication path redundancy. With it the file system can keep passing messages until it either recovers from network failures or it is failed over to a backup. Load balance for messages is also achieved to relieve network traffic. The deep learning-based smartphone imaging technique.
8	Jubair et-al[10], 2021, Jordan	Cross-sectional N=716	DL	Tongue	-	Specificity-84.5% Sensitivity-86.7% AUC-0.928	CNNs can aid in developing affordable integrated vision Deep systems for diagnosing oral cancer; however, they possess restricted memory and processing power. AI can improve oral cancer screening and early detection by broadening its accessibility and

Continued.

S. no	Author, year, country	Study Design/sample size	ML/DL	Type of cancer	Source of illumination	Statistical findings (AUC, sensitivity, specificity, etc)	Main outcome
							enhancing its effectiveness.
9	Bofan et al[7], 2021, India	Cross-sectional N =5025	DL	Oral cancer	Autofluorescence imaging White light imaging	Sensitivity-79%, Specificity-82%	The suggested dual-modality deep CNN approach aims to automatically classify images of malignancy and oral dysplasia. This technique efficiently detects cancerous images and dual-use modality oral dysplasia on mobile devices like smartphones and tablets.
10	González et al[12], 2021, Colombia	Cross sectional N=500	DL	Leukoplakia	_	Precision – 95%, Recall-75%, Accuracy - 94.12%, Specificity – 98.78%, F1 score - 83.33%, AUC-86.96%	The created model used CNN to detect various oral sores by using the pre-trained Mobile net V2 network from ImageNet, which includes a wide range of categories like plants, flowers, animals and objects, resulting in impressive classification results.
11	Welikala et al.[18] 2020, Malaysia	Cross-sectional N=2155 oral cavity images from 1085 individuals	DL	Oral cancer	_	Sensitivity – 85.71%, Specificity – 76.42%, Accuracy – 80.88%, F1score - 81.6%	The VGG models now offer a more consistent and trustworthy method, effectively demonstrating the capabilities of AI. Nonetheless, the alternative architectures present a greater capacity to learn intricate patterns and will yield better outcomes when our dataset expands.
12	Uthoff et-al[15], 2018, India	Cross-sectional N=From 5025 subjects, a total of 32,128 images, Case-control N=364 pairs	DL	Oral cancer	Autofluorescence, light emitting diode, white light imaging	AUC-0.908, sensitivity in remote specialist-0.8667, CNN-0.8875, specificity in remote specialist-0.9259, CNN-0.85	Creating and implementing a cost-effective, dual-purpose, smartphone-based imaging device for early identification of oral cancer in low- or middle-income nations. Healthcare workers and residents can utilize the equipment to capture Auto fluorescence imaging (AFI) and White light imaging(WLI) photos, which can be later sent to the cloud for analysis by Convolutional neural network (CNN) and diagnosis by experts from a distance.
13	Welikala et al[17], 2017, Malaysia	Cross-sectional N=2155 oral cavity images from 1085 individuals	DL	Oral cancer		F1 score - 41.8	Using ResNet-101 to classify images and employing Faster R-CNN for object detection. Image classification achieved an F1 score of 87.07% in detecting lesion photos while identifying images requiring referral reached a success rate of 78.30%. The identification of lesions necessitating referral had a 41.18% F1 score using object detection. Additional

Continued.

S. no	Author, year, country	Study Design/sample size	ML/DL	Type of cancer	Source of illumination	Statistical findings (AUC, sensitivity, specificity, etc)	Main outcome
							performance reports are provided based on the classification of the referral decision. Our early findings suggest that deep learning could successfully address this difficult problem.

DISCUSSION

The primary goal of this systematic review is to evaluate how well AI can detect and screen for oral cancer using images taken inside the mouth. Most of the research included in this systematic analysis showed that various AI models, such as machine learning and deep learning, are successful in detecting oral cancer with high sensitivity and specificity. Recent developments in algorithms enable the detection of oral cancer through a non-intrusive, effective approach that rivals the expertise of humans. Even with regular assessments from dental professionals, many cancers may go unnoticed until they have advanced significantly or become malignant. Experts can detect oral cancer by visually evaluating the clinical appearance of the lesion. AI offers a faster and more precise way to detect the early stages of oral cancer and may be seen as the most effective way to reduce the mortality rate from this illness. AI is gaining attention in the field of oncology for improving the accuracy and efficiency of identifying possible lesions during screening. In the systematic review, all selected studies included 2 studies that employed supervised machine learning, while deep learning techniques were used in 11 studies. Studies using deep learning showed sensitivity between 75% and 89.3% and specificity between 83% and 94.83%, whereas machine learning had sensitivity at 89% and specificity at 75%. Machine learning shows a range of changes, leading to uncertainty in the performance or results of machine learning. On the other hand, techniques that make use of deep learning yield trustworthy results. Regarding overall performance, deep learning shows the most favorable outcomes as suggested by the studies examined.

Uthoff et al, utilized smartphone data transmission power in their research to differentiate between suspicious and non-suspicious lesions using a deep learning method and probability scoring system.[14] They achieved a low risk of bias by successfully detecting an Area under curve (AUC) which is used to visualize the performance of multi-class classification of the image of 0.908. On the other hand, Jubair et al, created cost-effective integrated vision Deep systems for oral cancer detection, but their memory and processing capabilities are limited.[8] AI has the potential to enhance the accessibility and effectiveness of oral cancer screening, leading to an AUC of 0.928 which improves early detection. However, Dinesh et al, show that machine learning enables patients and general dentists to detect potential lesions such as OSCC and OPMDs that warrant a biopsy and immediate treatment.[7] This has shown positive outcomes in the early identification of potential abnormalities using clinical intraoral pictures. Another study by Fu et al, employed a detection network to generate one bounding box indicating the likely lesion from an oral image as input.[20] Based on the results of the detection in the first phase, the lesion region was identified and extracted as a potential area. After the candidate patch was submitted to a classification network, it generated a pair of confidence scores for patients with OSCC and controls, ranging from 0 to 1. The algorithm is unable to accurately forecast lesions outside of oral disease lesions due to the limited diversity and variability of oral disease lesion images used in training deep neural networks. The recommended AUC of the machine learning technique. The proposed machine learning was assessed in seven studies using AUC. The machine learning method being considered was assessed across seven distinct studies using the AUC metric. In the internal validation dataset's secondary analysis, the deep CNN demonstrated superior accuracy for oral cancer detection by achieving a 99.5% AUC score with photographic images. This review shows, based on the articles included, that machine learning displays higher average sensitivity and specificity.

CONCLUSION

This systematic review shows results from multiple studies examining how well AI algorithms can detect oral cancer using images captured on mobile devices. The diagnostic efficiency of AI models varies depending on whether machine learning or deep learning techniques are used. The studies indicate that machine learning's average sensitivity and specificity typically fall within the ranges of 89% to 92% and 75% to 82%, respectively, while the average sensitivity and specificity can also be found between 85.12% to 90.23% and 87.64% to 90%. As per the findings, machine learning shows higher precision than deep learning in detecting oral cancer. The results suggest that smartphone images are effective in diagnosing oral cancer.

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