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Artificial Intelligence in Oral Cancer: A Systematic Review

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Abstract

Introduction: Recent developments in Artificial Intelligence (AI), a novel technology that mimics human cognition, have gained worldwide scientific attention in cancer research. In oral cancer treatment, AI has promising effects on disease detection, prognosis prediction and management, particularly in studies involving squamous cell carcinoma, premalignant lesions and salivary gland tumors. This systematic review was conducted to critically evaluate the available evidence concerning AI's accuracy, sensitivity and specificity in oral cancer detection, diagnosis, prognosis and clinical management.

Methods: Original studies conducted on humans using AI technology and published in English were included. The studies included were conducted on patients with suspected/diagnosed oral cancer (any stage and grade) as the primary site. The search terminologies included "artificial intelligence," "oral cancer," and "oral squamous cell carcinoma." The studies were selected based on study and patient inclusion criteria. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol was used when searching databases, like PubMed and Google Scholar, in August and September 2023. The risk of bias assessment was performed using the JBI evidence synthesis tool and a risk score was calculated for all included studies. Due to heterogeneity among the selected studies, formal quantitative syntheses were not conducted.

Results: Of 775 records, 5 were critically appraised and included in this systematic review, with 611 subjects assessed. One of the 5 studies used a Supervised Vector Machine (SVM) and the rest used neural networks either alone or in combination with another modality/algorithm. The research studies have used both machine learning and deep learning algorithms, with the majority of them (4 out of 5 studies) using neural networks, which account for 90% of all the studies included in the systematic review. 60% of the studies present with low risk of bias. The sensitivity, specificity, accuracy and overall performance of all AI algorithms used in all the studies ranged from 45.5% and 84.8%, 54% and 85.3% and 59.9% and 82.05%, respectively.

Discussion: The heterogeneity among studies and the majority of included studies with moderate risk of bias are some notable limitations of this present systematic review. AI-based models aid clinicians in early cancer diagnosis, prognosis and treatment efficiency. They enhance proficiency in overall cancer care. They act as an adjunct to reduce the clinician's work burden and minimize inadvertent errors. Within the present limitations of the review and comprehensive search and analysis of the available literature based on five studies performed in a clinical real-time setting, we can conclude that utilizing AI (both machine learning and deep learning models) is effective in the early detection, diagnosis, management and prognosis of oral cancer. This is achieved irrespective of the AI model used. The systematic review protocol has been registered in the International Prospective Register of Systematic Reviews (PROSPERO) with ID Number: CRD42023461832.

Keywords: Oral Squamous Cell Carcinoma; Neural Network; Machine Learning; Head and Neck Squamous Cell Carcinoma; Deep Learning, Artificial Intelligence

Introduction

Oral cancer (OC; International Classification of Disease [ICD-10-CM Codes C00-C14]) is a subtype of head and neck cancer and a serious global public health concern, ranking as the 16th most common cancer worldwide. In 2022, approximately 389,846 new cases were reported globally [1,2]. Oral and Oropharyngeal Squamous Cell Carcinoma (OPSCC) outcomes are most strongly influenced by early diagnosis; however, most of these tumours are discovered late, leading to poor diagnosis. The difficulty in diagnosing oral lesions arises from the reliance on subjective evaluations of clinical characteristics, including colour, texture and consistency, which result in mild lesions that might be mistaken for other conditions. Hence, the application of Artificial Intelligence (AI) in the fight against cancer has advanced rapidly. Potential therapeutic entanglements can be relieved by understanding AI advancements. AI for treating oral malignant growths can help with the current difficulties in disease identification, prognosis prediction and effective management.

AI, which imitates human cognitive processes, represents an innovation leap and has captured the attention of scientists worldwide [3]. It also offers the chance to create novel approaches that work in conjunction with established methods to increase the accuracy of OC and Oral Potentially Malignant Disorders (OPMD) identification as well as the ability to forecast the path of precancerous/cancerous lesions from retrospective data [4]. AI models can be used to curate various data streams for cancer detection to make decisions, determine risk and send patients to professionals. By encouraging early detection and efficient treatment strategies, these programs may reduce mortality rates [5]. For data analysis on these platforms to provide precise and costeffective diagnoses, large data volumes and resources are needed. Before these models can be securely included in standard clinical procedures, they must be refined to attain the best possible accuracy, specificity and sensitivity. Regulatory frameworks are also necessary to implement these models in clinical practice [5,6].

This systematic review was conducted to critically evaluate the available evidence concerning the accuracy, sensitivity and specificity of AI in oral cancer diagnosis, prognosis and effective clinical management.

The systematic review protocol was registered in the International Prospective Register of Systematic Reviews (PROSPERO) (ID number CRD42023461832). The Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA 2020) guidelines were followed when reporting this review [7]. This study aimed to answer the question: Are artificial intelligence-based models effective in oral cancer detection, diagnosis, management and prognosis? Search Strategy An electronic search was conducted using databases PubMed and Google Scholar. The following keywords were used for identifying the articles: artificial intelligence, oral cancer and oral squamous cell carcinoma. The electronic database PubMed was used to do the article search utilizing Boolean operators (AND, OR), along with a filter for clinical trials, randomized clinical trials and a language filter for English. For Google Scholar, a filter for 'keywords only in the title of the article' was used. The search was performed independently by two qualified authors. A preliminary search of PROSPERO was conducted and no current or underway systematic reviews on the topic were identified.

Research Question

The focused question was developed by PICO (problem/patient, intervention/indicator, comparison and outcome) presented in Table 1 and a search was conducted based on the PICO criteria.

Research Question	**Are Artificial intelligence-based models effective in oral cancer detection, diagnosis, management, and prognosis?**
Population	Patients suspected/diagnosed with oral cancer at any stage and grade
Intervention	AI-based models designed for oral cancer detection, diagnosis, therapeutics, and prognosis
Comparison	None/ Conventional modality if data persists
Outcome	**Main outcomes**
	Efficacy of Artificial intelligence - based models in oral cancer diagnosis, management and prognosis.

	1- Early diagnosis (radiological as well as pathological)
	2- Precise surgical management of oral cancer reducing the rate of recurrence
	3- Early and accurate identification of nodal metastasis
	4- Prediction of survival rate of patients
	5- Prediction of possible outcome of surgical procedure performed and/or non-surgical therapy provided
	Additional Outcomes
	Efficacy of AI-based models in predicting and managing oral cancer-associated complications and post-therapeutic complications like oral mucositis and osteoradionecrosis of the jaw.
	Measures of outcome based on accuracy, sensitivity, specificity stating overall performance and P value less than 0.05.

Table 1: Description of the PICO (P = Population, I = Intervention, C = Comparison, O = Outcome) elements.

Study Selection

A total of 775 articles were obtained through the electronic database search for initial consideration. The initial selection of articles was based on their relevance to the research area, as well as the title and abstract. To ensure that there were no duplicated articles, two reviewers (R1 and R2) involved in the initial search checked all articles for duplicates, leading to the removal of 2 duplicates. A total of 773 records were screened and out of that, 700 were excluded for non-reliability. Total reports sought for retrieval were 73. Subsequently, 73 articles were thoroughly reviewed for data selection and 11 articles were assessed for eligibility in Fig. 1 (PRISMA).

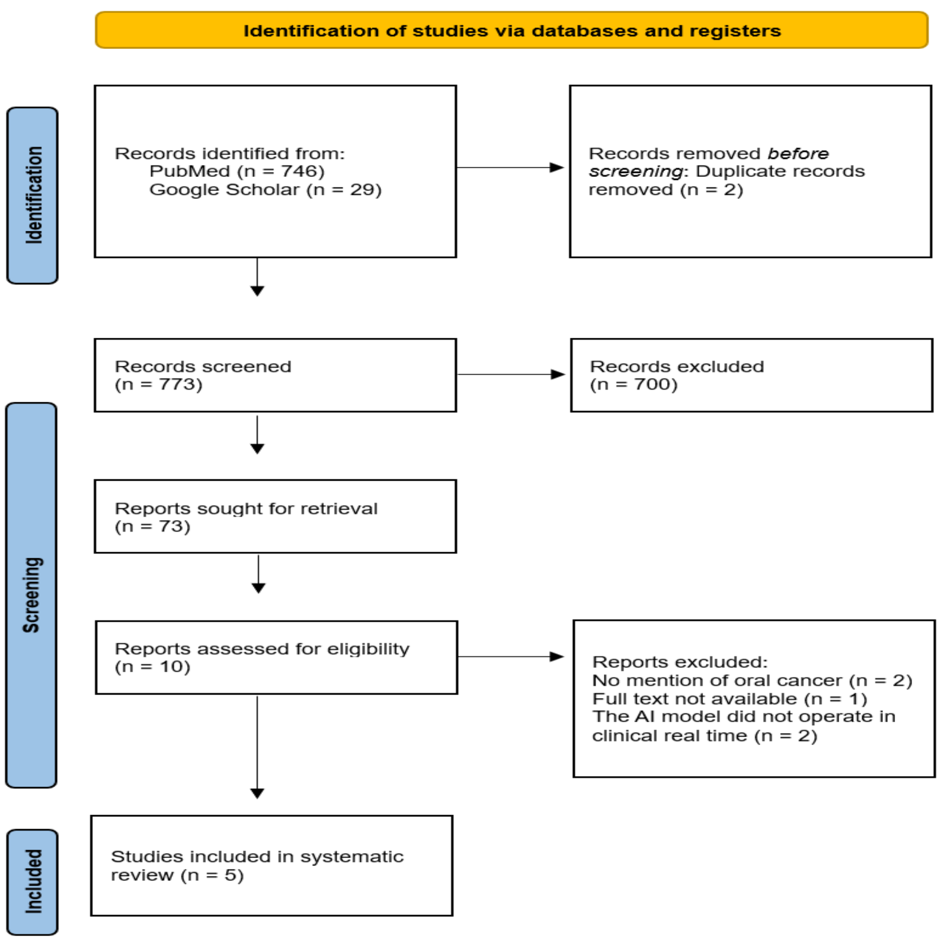

Figure 1: PRISMA diagram for study selection.

Inclusion and Exclusion Criteria

Inclusion Criteria

- Articles of original research, like clinical trials, randomized controlled trials, observational/cross-sectional studies, case-control studies and cohort studies
- Research conducted on human studies
- Published in the English language
- Studies with AI technology (AI-based models) for detecting oral cancer should be the main topic of the research paper
- Studies presenting results on AI model efficacy (diagnostic and prognostic prediction accuracy) and/or comparisons with human diagnostic performance.
- Studies where AI Images or datasets are used as input for research articles
- Studies published till July 2023 and studies with the availability of full-text

Exclusion Criteria

- Studies without a clear description of the AI model used
- Studies with insufficient reporting on the designated outcomes
- Review articles like narrative and systematic reviews, case reports, case series, textbook chapters, expert opinions, animal studies and survey studies

The guidelines were followed to guarantee the rigor and quality of the chosen research while reducing any biases and mistakes.

Patient Inclusion and Exclusion Criteria

Inclusion Criteria

The age of the patient between 18 to 80 years including both males and females; patients suspected/diagnosed with oral cancer at any stage and grade; patients with primary cancer site being oral cavity; Site of oral cancer: oral cavity, tongue, buccal mucosa, hard and soft palate, lip and other parts of the oral cavity (ICD - 10, C00, C01, C02, C03, C04, C05).

Exclusion Criteria

Patients presenting with oral cancer as the secondary site; patients with oropharyngeal cancer; Children in the age group being 0≤17 years.

Data Extraction

After applying the inclusion criteria, initially, 73 articles were selected for analysis. Two reviewers, R1 and R2, independently performed an advanced search and relevant filters were put in search databases (PubMed and Google Scholar) and critically evaluated. A Microsoft Excel sheet was created using the data that was 2 of 7 extracted from the selected articles. The data from the selected articles were extracted and entered into a Microsoft Excel sheet. These data included authors, year of publication, study design, AI algorithm, study objective, study factor, sample number/size, sample type, comparison if any, study effect, conclusions and limitations according to authors. Basic screening of articles was done by assessing the abstracts. R3 (reviewer) crosschecked the included studies by individually assessing the searches performed by R1 and R2. In 2 articles there was no specific mention of oral cancer and its associated sites, which led to the exclusion of those studies. After reading the full text of the article, studies that did not fit all the criteria along with the duplicates were excluded. The decision column included numbers 1 and 0 (1 was for study included and 0 for study excluded). R1, R2 and R3 independently screened all the included studies and looked for Risk of Bias (ROB). A common Google document was created, which all three authors could view, edit and comment on. Consequently, a total of 5 studies that were thought to be possibly suitable for this systematic review underwent critical analysis. Quality Assessment Three impartial reviewers evaluated the methodological quality of the eligible papers using the Joanna Briggs Institute's (JBI) Critical Appraisal Checklist for Qualitative Research [8].

Results

Qualitative data was retrieved following a thorough analysis of the five articles. A growing trend of reporting on the application of AI for OC detection, diagnosis, treatment and prognosis prediction was found in most of the research.

Characteristics of Included Studies

The articles included in this systematic review were published in English language. The 5 studies were conducted in China, the USA, India, Malaysia and the Netherlands [9-13]. Out of 5 studies, 4 were conducted in the 21st century (2023, 2004, 2018, 2010) except for 1 which was conducted in the 20th century (1998) [9-13]. All studies were conducted in a clinical real-time setting. Qualitative Synthesis of the Included Studies The primary uses of AI technology include differentiating between normal and malignant tissues, establishing an early OSCC diagnosis, predicting patient survival, identifying people at risk for developing oral cancer, detecting cervical lymph node metastasis in OSCC patients and oral mucositis prediction in patients with head-and-neck cancer post-chemotherapy [9-13]. In this systematic review, 5 studies were reported using Entropy-Gradient Support Vector machine (EGSVM), Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANN), Logistic Regression (LR), Fuzzy Neural Network (FNN) and Fuzzy Regression (FR) as depicted in Table 2 either alone or in comparison.

Statistical Findings

In comparison to manual qualitative analysis, Dong F, et al., discovered that the EGSVM-based automatic analysis showed greater sensitivity (84.8% vs. 71.7%), specificity (77.3% vs. 72.7%), accuracy (81.1% vs. 72.2%), positive predictive value (79.6% vs. 73.3%) and negative predictive value (82.9% vs. 71.1%) [9].

According to TJ Bryce, et al., the ANN's area under the receiver operating characteristic curve (Az) was 0.78 +/- 0.05 when employing the best feature sets, demonstrating a more accurate overall performance than LR (Az = 0.67 +/- 0.05, p = 0.07). The ANN was 72% specific at 70% sensitivity, while the LR was 54% specific (p = 0.08). The ANN was 72% sensitive at 70% specificity, but the LR was 54% sensitive (p = 0.07). Az for LR reduced [Az = 0.61 +/- 0.06, p < 0.01 (ANN)] when both models employed the five predictive factors that an ANN found to be the most effective. When the three variables that work best for LR were used, the models performed equally well. The best ANN also outperformed staging [Az = 0.60 +/- 0.07, p = 0.02 (ANN)] in comparison [10].

Rosma, et al., conducted performance comparisons between two artificially intelligent prediction methods and a team of oral cancer specialists' predictions. The sensitivity and specificity of the prediction were evaluated. For Fuzzy Neural Network (FNN) models, the mean accuracy, sensitivity and specificity were 59.9, 45.5 and 85.3; for doctors' predictions of oral cancer, they were 63.1, 54.2 and 78.6; and for fuzzy regression prediction models, they were 67.5, 69.0 and 64.7. The areas under the receiver operating characteristic curves show how accurate the models are at making predictions. For single-input and two-input predictor sets, there were no appreciable differences in the prediction performance among the three models. However, when the number of the input predictor set was increased, Fuzzy Regression (FR) and fuzzy neural networks outperformed oral cancer doctors [12].

In a study, Thukral, et al., used a computer-aided deep learning model to distinguish between Grade 0 and Grade 1 oral mucositis following cancer treatment. They discovered that the model had a 100% training accuracy and an 82% testing accuracy, which were both promising outcomes. As a result, the proposed model's false-negative rate significantly decreased, showing increased performance. In general, researchers discovered that the model's prediction accuracy for Grade 0 or I mucositis was 82%. A classification accuracy of 82.05% means that roughly 82.05% of the dataset's instances were properly classified by the model [11]. Principal Components Analysis (PCA), artificial neural networks and red/green intensity ratios were used in a study by Diana CG de Velde, et al., to distinguish between benign and (pre-malignant lesions using four normalization procedures. For separating malignant from healthy tissue, the Receiver-Operator Characteristic Areas Under the Curve (ROC-AUCs) range from excellent (0.90 to 0.97). However, for all approaches (0.50 to 0.70), the ROC-AUCs are too low to distinguish between benign and (pre)-malignant mucosa. There are some statistically significant changes between the surrounding/contralateral tissues of (pre-)malignant lesions and benign and healthy tissue. Cancers can be successfully distinguished from healthy mucosa (ROC-AUC>0.9). However, utilizing their techniques, autofluorescence spectroscopy is unable to differentiate between benign and visible (pre-)malignant lesions (ROC-AUC0.65). Significant differences in surrounding/contralateral placements of lesions and healthy tissue have been reported; these changes could be useful for invisible tissue alteration detection [13].

Risk of Bias Assessment

The Risk of bias assessment is a very crucial stage in this systematic review. Two reviewers R1 and R2 performed ROB independently. The ROB was performed using the JBI Risk of Bias Assessment Tool and the scoring percentage was calculated accordingly to each included study (Table 3). A separate checklist is provided for every study design, that aids in calculating JBI risk score. Out of 5 studies analysed, 3 presented a moderate risk of bias i.e. 60% of the total included studies [10,12,13]. The rest of the 40% presented a low ROB [9,11]. None of the included studies presented high ROB.

Data Synthesis

The collected data and main findings are presented as narrative synthesis. Due to the heterogeneity amongst the selected studies, formal quantitative syntheses were not conducted.

Sl No	Authors	Year of publication	Study design	AI Algorithm	Objective of the Study	Study Factor	Sample number	Sample type	Comparison if any	Results Effective, Non-Effective Neutral	Authors' Suggestions/Conclusions	Limitations stated by authors
1	Dong F et al (7)	2018	Prospective clinical trial	SVM (EGSVM)	This study aimed to evaluate the diagnostic performance of a non-radiating, noninvasive infrared (IR) thermal imaging system in the detection of cervical lymph node metastasis from oral cavity cancer.	Detection of cervical lymph node metastasis	Oral cavity cancer patients suspected of having cervical lymph node metastasis, underwent IR imaging of the neck prior to neck dissection = 90 Post Physical examination and CT results: a) 46 = Clinically suspected LN metastasis; b) 44 = Clinically no suspected metastasis	IR thermal imaging Vs CT	Analysis of the IR images was performed by two methods: manual qualitative analysis Vs automatic analysis by an entropy-gradient support vector machine (EGSVM).	Effective	The EGSVM-based infrared thermal imaging system is a promising non-radiating, noninvasive tool for the detection of lymph node metastasis from oral cavity cancer. The EGSVM-based infrared thermal imaging system has several advantages as a screening and diagnostic tool for the detection of cervical lymph node metastasis from oral cancer. First, infrared thermal imaging is completely risk-free. It passively captures thermal radiation emitted by the human body, as there is no need for ionized radiation, contrast agents or any invasive procedures. Second, compared with other medical imaging examinations, IR examination is inexpensive due to the low-cost IR camera that is used. In addition, IR image capture and automatic image analysis can be completed in less than one minute each, allowing results to be obtained quickly.	1) This is a patient-based diagnosis of cervical lymph node metastasis from oral cavity cancer. Metastatic lymph nodes and the vascular abnormalities they cause can both result in deviations in heat, which provides the basis for the use of infrared imaging. 2) Location of the abnormal area in two-dimensional space, this becomes difficult to precisely identify the lymph nodes within this area. Due to its limitations in identifying the exact anatomical localization of lesions, this method is currently more suitable for use as a screening tool. We anticipate that the EGSVM-based infrared thermal imaging system will play a role as a fast screening tool for detecting of cervical lymph node metastasis from oral cavity cancer in resource-limited environments. 3) This study extracted only one feature for automatic classification; the performance of the model can be improved with additional useful features. 4) Additionally, more patients are needed to evaluate the diagnostic performance of this method in a multi-center clinical trial before it can be widely used for the detection of cervical lymph node metastasis from oral cavity cancer.
2	Bryce TJ et al (8)	1998	Randomized Clinical trial	ANN, LR	This study was performed to investigate the feasibility of predicting survival in squamous cell carcinoma of the head and neck	Predicting 2-year total survival	Patients with histologically proven, previously untreated SCCHN without distant metastases and involving either an advanced primary tumor ($T3)	14 prognostic variables: treatment arm of the trial, T and N stage, tumor site, resectability,	ANN Vs LR	Effective	An ANN modeled 2-year survival in this data set more accurately than LR or staging models and employed predictive variables that could not be used by LR. Further work is planned to confirm these results on larger patient samples, examining longer follow-up to incorporate treatment type into the model.	Data set employed in this study was relatively small

					(SCCHN) with an artificial neural network, and to compare ANN performance with conventional models.		or advanced cervical lymphadenopathy (N3) = 95	and size, age, sex, and race, Karnofsky performance status, white blood cell count, hemoglobin, the presence or absence of pain as a presenting symptom, and the presence or absence of concomitant medical problems				
3	Thukral R et al (9)	2023	Prospective Observational Study	CNN	to assess the accuracy of the automated computer-aided deep learning approach in predicting the occurrence of oral mucositis in patients with HNSCC undergoing radiotherapy alone or with concurrent chemotherapy.	predicting oral mucositis at an early stage post chemoradiotherapy	patients with HNSCC planned for radiotherapy = 5 Thermal images = 386	Thermal images		Effective	The study highlights the potential of thermal imaging and a convolutional neural network model for automated classification of thermal images associated with mucositis in patients with HNSCC	Patients with Grade II or higher mucositis were not included in the study. While this may limit the applicability of study findings to patients with more advanced grades of mucositis, this strategy allows to focus specifically on the prediction and classification of patients with very early mucositis.
4	Rosma, M. D et al (10)	2010	Case Control Study	FNN, FR	This study is aimed at evaluating the ability of two artificial intelligent prediction models namely FR and FNN models to predict the likelihood of an individual developing OC on knowledge of their risk habits and demographic profiles.	Risk of developing oral cancer based on habits	Newly diagnosed oral cancer patients = 84 Non-cancer subjects = 87	Predicting variables: Risk habit factors such as betel quid and tobacco chewing, cigarette smoking, alcohol drinking as well as patients'	Performances of the two artificial intelligent prediction models (FNN, FR) Vs prediction made by a group of oral cancer clinicians.	Effective	The findings of this study suggest that both FR and FNN models provide good alternative to human expert prediction in predicting oral cancer susceptibility.	

								demographic profiles including age group and gender				
5	de Veld DC et al (11)	2004	Case Control Study	ANN	To compare algorithms for oral lesion classification (Premalignant, benign or malignant) and also examine the potential for detecting invisible tissue alterations	Early detection of oral premalignant and malignant lesions	patients with oral lesions = 155; healthy volunteers = 95	Autofluorescence spectra	PCA Vs ANN Vs red/green intensity ratio	Effective (In distinguishing all lesions or cancerous lesions from healthy oral mucosa); Not Effective (In separating benign from (pre-)malignant lesions)	Study shows statistically significant differences between surrounding/contralateral tissues of benign and healthy tissue and of (pre-)malignant lesions are observed. We can successfully separate healthy mucosa from cancers. However, autofluorescence spectroscopy is not able to distinguish benign from visible (pre-)malignant lesions using our methods. The observed significant differences between healthy tissue and surroundings/contralateral positions of lesions might be useful for invisible tissue alteration detection.	

Table 2: Characteristics of included studies.

Author		JBI Risk Score	Risk Percentage	Risk Of Bias (ROB)
Thukral R [9]		5⁄5	100%	Low
Diana C G de Veld MS [11]		3⁄5	60%	Moderate
Rosma MD [10]		4⁄7	57%	Moderate
Fan Dong CT [7]		8⁄8	100%	Low
T J Bryce MWD [8]		4⁄8	50%	Moderate
*Criteria used to rank the risk of bias i) ≤49% = high risk of Bias ii) 50% and 69% = Moderate risk of Bias (3 studies) iii) Above 70% = low risk of Bias (2 studies)				

Table 3: Risk of bias assessment using the JBI checklist.

Discussion

Most of the studies included in this systematic review show a low risk of bias. There are both Machine Learning (ML) and Deep Learning (DL) models used in the included studies. In one of the studies DL model has been specifically used in image classification. Out of 5 studies, 2 have used artificial neural networks in diagnosing/assessing oral cancer, 1 has used a Support Vector Machine, 1 has compared two AI models - Fuzzy Neural Network prediction model vs. fuzzy Regression Prediction model and the other has used Deep Learning model [9-13]. Machine learning with maximization (support) of separating margin (vector), called Support Vector Machine (SVM) learning, is a potent AI classification tool that is widely used in the field of cancer. SVM was proposed by Vapnik. SVMs are among the most effective and reliable classification, density estimation, novelty detection and regression methods. Among scholars, pattern recognition is a very popular and busy study area and the SVM has been playing a vital role in this area [14-16].

The Study performed by Dong F, et al., used Support Vector System (EGSVM) based infrared thermal imaging system and compared it with CT as a diagnostic and efficient screening tool for detecting metastasis to cervical lymph nodes from oral cancer. In comparison to manual qualitative analysis, it was found that the computer-aided diagnostic method employing the EGSVM model was more accurate at detecting lymph node metastases. The EGSVM-based infrared thermal imaging system showed greater sensitivity and was not inferior to contrast-enhanced CT ($P < 0.05$). The authors have provided important justifications for why they believe that an EGSVM-based approach is superior to a manual qualitative analysis. it's crucial to recognize the vascular changes that are associated with tumours since they are a sign of nodal metastasis. One of the main disadvantages of manual qualitative analysis is that the minor vascular changes could not be visible to the human eye which can be overcome by using computer aided EGSVM system, reduced inter-observer variability and rapid analysis of a huge number of images to increase efficiency. are most important benefits of the computer-aided EGSVM system that enhances overall diagnostic performance [9].

An ANN is a theoretical mathematical ML model of the human neural network. It is a method of processing information that is based on the design and operation of the human neural network. The use of ANNs is growing increasingly widespread as neural network technology advances and so are the application domains they can be used in. An ANN is a type of computer network system that replicates the human neural structure. It connects a large number of artificial neurons that are relatively independent to create a network that functions similarly to how organic nerves process information to solve issues. The first ANN for logic operations was proposed in 1943 by McCulloch and Pitts. Hebb proposed a set of guidelines in 1949 that replicate how the human nervous system develops [17].

ANNs have the following characteristics: 1- The capacity for self-organization and self-learning: It may modify and adapt its structure by interaction with the outside world; powerful promotion potential; 2- Highly parallel: Many similar or independent operations can be carried out concurrently; 3- Strong information synthesis ability: It can process both quantitative and qualitative information and can coordinate numerous input information fusion and multimedia technologies [18]. As they require less intrusive procedures and require less interpretation of imaging method data, neural networking technologies may be utilized to diagnose cancer more quickly and accurately than conventional approaches. Furthermore, neural networks have been trained to analyze each patient's prognosis and treatment strategy with a level of precision that rivals that of skilled medical professionals [19].

Bryce et al and colleagues compared ANN with logistic regression in predicting the survival of patients treated with irradiation with and without concurrent chemotherapy for advanced carcinoma of the head and neck. The study results showed accurate overall performance by the best ANN model compared to the best logistic regression model. The results were equivalent when three predictive variables were used. However, when a five-variable set was used by both models, it worked well for the ANN and it performed noticeably more accurately than logistic regression. This implies that, in contrast to logistic regression, the ANN was able to detect and utilise the complicated relationships between this set of predictive variables and survival. Additionally, the ANN model outperformed the AJCC staging model substantially more correctly. The staging model is constrained to a small number of classification groups and utilizes only TNM variables.

As a result, it is limited in how well it can forecast the relative prognoses of specific patients given a range of different predictive variables. The higher prediction value of the ANN model in the current investigation may be explained by the ANN model's capacity to recognize and apply predictive characteristics other than the TNM variables and to categorize each patient separately. The ANN model outperformed the logistic regression model in this investigation as ANN is a nonlinear, nonparametric method and is better able to identify and represent complicated predictive patterns. Although logistic regression is a linear technique, a neural network model's structure can be as complicated as desired and is chosen based on how well it represents the training data [10].

Convolutional Neural Networks (CNNs), a subclass of artificial neural networks, are now the most popular choice for many computer vision tasks. Lesion detection, classification, segmentation, image reconstruction and natural language processing are only a few of the fields that have used this AI algorithm. CNN is a deep learning model type and very well handles data with a grid pattern such as photographs. It is incredibly effective at processing images. CNN was created with inspiration from how the animal visual cortex is organised and is intended to automatically and adaptively learn spatto high-level patterns [20].
To automate the classification of thermal pictures related to Grades 0 and I mucositis, Thukral R, et al., and colleagues 2023 investigated the possibilities of utilizing thermal imaging and a deep learning model. They discovered that the model had an 82% accuracy rate for predicting Grade 0 or I mucositis. By automating the classification of thermal images, their method can be used to identify and monitor mucositis in patients with HNSCC undergoing radiation therapy. This might allow for prompt interventions, individualized treatment plans and less harm to the essential organs nearby. In their work, they used "nearest-neighbor interpolation" as a pre-processing step to get the thermal images ready before feeding them into the deep-learning

neural model. This pre-processing method was used to resize the photographs while preserving their original content. We accomplished two significant goals by downsizing the images: we improved computing efficiency while maintaining the robustness of the model. Smaller images demand less processing power and memory, which improves computational efficiency and speeds up model inference and training. The scaling procedure also assisted in preserving the fundamental patterns and features inherent in the photos, ensuring that the model could learn and predict accurately.

The computational efficiency and simplicity of "nearest-neighbor interpolation" are its main benefits. When constructing the scaled image, this method chooses the closest pixel value from the original image, which uses a minimal amount of computational resources. The pre-processing procedures chosen rely on the particular needs of the study and the features of the dataset. A non-contact, non-invasive technique for spotting early temperature fluctuations within the mouth mucosa is thermal imaging. This portable imaging gadget is extremely practical and versatile.

This model can be used to reliably forecast the occurrence of mucositis since it has a low false-negative rate, which increases the model's effectiveness. The primary objective of the suggested model was to reduce the incidence of false-positive and false-negative outcomes, which are important variables affecting any diagnostic system's efficacy. False negatives happen when the model is unable to detect mucositis in the image that contains the condition, whereas false positives happen when the model mistakenly classifies a healthy instance as mucositis-positive. The high accuracy of deep learning models in image classification tasks like mucositis prediction over typical machine learning models can be attributed to a number of factors. First, deep learning models are more suited to finding patterns in medical images since they are made primarily for image analysis jobs and are capable of extracting complicated characteristics from photos (including thermal images). Second, deep learning models employ convolutional layers that can recognize features in images like edges and corners at various spatial scales, enabling them to gather more specific data about the image. Third, back-propagation is used to train deep learning models, enabling them to modify their weights and biases to improve their performance on training data. Fourth, pooling layers are used by deep learning models to down-sample the image, hence lowering the model's parameter count and reducing the likelihood of overfitting. Deep learning models are generally quite good at image analysis tasks and can produce extremely accurate predictions of the severity of mucositis because to the combination of these features and methods. The demand for realtime observation is effectively met by the acquisition and processing of thermal pictures, which takes only five to six minutes in total. The suggested approach offers an easy-to-use, risk-free and non-invasive early intervention diagnostic tool for assessing the grade of mucositis [11]. Using four normalization strategies, de Veld DC, et al., and colleagues examined Principal Components Analysis (PCA), artificial neural networks and red/green intensity ratios to distinguish between benign and (pre-)malignant lesions. primarily to classify lesion types. They also looked at the possibility of employing autofluorescence spectra to identify invisible tissue alterations. The authors observed that while all lesions or malignant lesions could be distinguished from healthy oral mucosa, the pertinent clinical question could not be addressed. Their techniques failed to distinguish between benign and (pre-)malignant lesions. They believe that this is partly because of the complexity of the oral cavity compared to other organs, where autofluorescence spectroscopy has been used more successfully for the staging of lesions using comparable excitation [13].

Rosma, et al., conducted a study that aims to assess how well two artificially intelligent prediction models fuzzy regression and fuzzy neural network models can forecast a person's likelihood of acquiring oral cancer given their risk factors and demographics. For single-input and two input predictor sets, there were no appreciable differences in the prediction performance among the three models. When the number of input predictors was increased to three and four, however, fuzzy regression and fuzzy neural network outperformed oral cancer clinicians. The topic of discussion is based on systems that could perform better than experts. This research contends that the most effective system may provide outcomes through the fusion of particular domain expert knowledge with machine learning [12].

Conclusion

The application of Artificial Intelligence (AI) in oral cancer has advanced considerably over the past decade, demonstrating its potential to transform clinical practice. AI-based models have shown promise in facilitating early diagnosis, improving prognostic accuracy and enhancing treatment planning, thereby contributing to greater efficiency and precision in cancer care. Beyond supporting clinical decision-making, AI serves as an adjunct tool to reduce clinician workload and minimize the risk of human error. Drawing from a comprehensive analysis of five real-time clinical studies, it may be concluded that both machine learning and deep learning approaches demonstrate effectiveness in the early detection, diagnosis, management and prognosis of oral cancer, independent of the specific AI model applied. Future research with larger, multicentric trials is warranted to address existing gaps in detection by AI model and facilitate the integration of AI into routine oncology practice.

Conflict of Interest

In compliance with the ICMJE uniform disclosure form, all authors declare the following: Payment/services info: All authors have declared that no financial support was received from any organization for the submitted work. Financial relationships: All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. Other relationships: All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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Data Availability Statement

Not applicable.

Ethical Statement

The project did not meet the definition of human subject research under the purview of the IRB according to federal regulations and therefore, was exempt.

Informed Consent Statement

Informed consent was taken for this study.

Authors' Contributions

All authors contributed equally to this paper.

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