International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 2635-2651
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Advancements in Artificial Intelligence for Oral Cancer Diagnosis

Sakshi Taaresh Khanna[1*], Sunil Kumar Khatri[2], Neeraj Kumar Sharma[3]

[1]Amity Institute of Information Technology, Amity University, Amity Road, Sector 125, Noida – 201301, Uttar Pradesh, India.
*** Corresponding Author Email:** sakshitaareshkhanna@gmail.com – **ORCID:** 0009-0006-2936-8708

[2]Amity University, Amity Road, Sector 125, Noida – 201301, Uttar Pradesh, India.
Email: skkhatri@amity.edu – **ORCID:** 0000-0003-4373-9000

[3]Department of Computer Science, Ram Lal Anand College, (University of Delhi), Benito Juarez Marg, New Delhi – 110021, India.
Email: neerajksharma100@gmail.com – **ORCID:** 0000-0003-3663-8914

Article Info:

DOI: 10.22399/ijcesen.1666
Received: 17 February 2025
Accepted: 22 April 2025

Keywords :

Machine Learning,
Deep Learning,
Oral Cancer Diagnosis,
Artificial Intelligence.

Abstract:

Cancer has been considered an incurable disease since its inception and has had an intimidating effect on mankind. Rapid technological advancement and medical breakthroughs have indeed thwarted its threat. Cancer is curable, provided it gets detected in the nascent stage. A growth or sore in the mouth that doesn't heal is the first sign of oral cancer. Despite the advanced radiation therapy and chemotherapy available, the fatality rate projects a grim picture with enormous scope for improvement. This study aims to broaden the use of artificial intelligence in the early stages of oral cancer detection. For papers that used artificial intelligence to diagnose oral cancer, a search was made between January 2018 and June 2024. Based on diverse image kinds and the use of artificial intelligence, 50 studies were included in diagnosing or detecting oral cancer. These studies were divided into different categories due to the heterogeneity of their data and the wide variety of algorithms used for analysis based on artificial intelligence. The precise prediction and identification of the onset of oral cancer may be greatly aided by artificial intelligence. Albeit, various chronological issues require attention alongside advances in artificial intelligence techniques to safely integrate with everyday clinical procedures and practices. This paper intends to act as a detailed guide for all to develop a system of similar thought processes.

1. Introduction

Cancer, a noxious disease claims millions of lives annually at a global level. Oral cancer is one such isoform that is generally triggered due to a few impetuous and sloppy day-to-day activities of people which usually can be mitigated through self-discipline. With almost 3,55,000 new incident cases every year recent global estimates position carcinomas of the lip and oral cavity (often referred to as "oral cancers") as the 16th most common malignant neoplasm around the globe. Squamous cell carcinomas account for more than 90% of oral cancers, and two-thirds of cases—50% of them in South Asia—occur in developing countries. Approximately 100,000 incident cases annually are from India alone [1]. Oral cancer covers cancers of the mouth and the back of the throat. Oral cancers tend to develop on the tongue, sublingually, the tissue lining the mouth and gums, at the lower part of the tongue, and in the upper part of the throat towards the back of the mouth. In 2020, the diagnosis and remedy of cancer were adversely affected by the coronavirus disease (COVID-19) pandemic. Minimal access to care because of community spread and fear of COVID-19 exposure resulted in delays in diagnosis and treatment that led to a short-term drop in cancer incidence followed by a surge in advanced-stage disease and, consequently higher fatality. Delayed detection of cancer leads to a stunted survival rate, less effective treatment response, and exponentially high cost. Enhanced information on the disease along with underlying symptoms and risks shall have a phenomenal impact on diagnosis and accelerating identification of malignancy symptoms that hitherto would be untraced or under-evaluated. It is pertinent to isolate lesions that might transform malignantly. Visual screening of the oral cavity has received a phenomenal response as an effective and prudent strategy for identifying such lesions to comprehensively sublime oral cancer fatality. The delayed diagnosis of oral cancer is due to myriad interconnected factors. Distinguished authors have isolated problems requiring corrective actions: a. Delayed symptoms detection b. sublime knowledge of oral cancer c. medical care delay [2,3]. Artificial Intelligence is having a tremendous impact on ameliorating diagnostic precision and could be path-breaking in an all-encompassing way (from screening to treatment). Another sub-segment of artificial intelligence is machine learning. It deploys computational methods for identifying patterns, deciphering actionable insights, and foretelling predictions based on historical data. A sub-discipline of machine learning is deep learning, wherein artificial layered networks are created using structured algorithms. Present-day studies have showcased the high accuracy and tremendous potential of deep learning, leading to its widespread adoption. Artificial intelligence has contributed immensely towards development in oncology. Numerous reviews have cited its usage in the timely detection of potentially malignant diseases and oral cancer. The primary mode of diagnosis presently revolves around analyzing and processing images. The focus is on deciphering relevant information for identifying relevant indicators of pathological interest. Primary examination imaging paradigms play a key role in deriving clinical data using artificial intelligence or machine learning techniques. The kinds of data used include Radiomic data, ultrasound images, computed tomography scans, magnetic resonance images, positron emission tomography, histological data, immunohistochemical data, multispectral narrow-band images, Raman spectroscopy images, infrared thermal images, etc.

The incidence and fatality rates of oral cancer are both on the rise, making this a big problem for people's health all around the world. The ability to diagnose cancer at an earlier stage is one of the most important factors in improving patient outcomes and survival rates. Traditional techniques of diagnosing oral cancer include a heavy reliance on the experience and judgment of doctors, which can result in significant variances in accuracy as well as delays in diagnosis. The incorporation of artificial intelligence holds tremendous promise for resolving these issues and bringing about a revolution in the diagnosis of oral cancer. Artificial intelligence approaches, such as machine learning and deep learning algorithms, have shown impressive capabilities in the processing of massive volumes of medical data, the extraction of relevant patterns, and the provision of reliable and efficient diagnostic help. We can develop advanced decision support systems that improve diagnostic accuracy, facilitate early detection, and enable personalized treatment strategies by harnessing the power of artificial intelligence. These systems can leverage the potential of large-scale datasets containing information on oral cancer, such as patient records, medical images, and genetic information. These datasets can be used to develop these advanced decision support systems. The urgent need to close the existing diagnostic chasm between traditional approaches to oral cancer treatment and the rapidly developing capabilities of artificial intelligence is what prompted the authors to conduct this study. This research endeavors to investigate the applicability of artificial intelligence-based models to the process of oral cancer diagnosis and, ultimately, to enhance both the quality of patient treatment and the outcomes.

One limitation of this literature review paper is the reliance on available published studies and databases. The scope of this literature review focused primarily on studies published up until June 2024. Therefore, newer research findings or emerging trends in the field may not have been fully captured in the analysis. Future studies should consider including more recent publications to provide a comprehensive overview of the advancements in oral cancer diagnosis using artificial intelligence and also strive to include studies from diverse populations to ensure a more thorough understanding of the effectiveness of AI-based approaches for oral cancer diagnosis. Due to resource and time constraints, the articles published in English were focused on. This literature review paper aims to synthesize and analyze the existing evidence on the use of AI in oral cancer diagnosis. However, it is important to acknowledge that the quality and methodological rigor of the included studies varied, which may impact the overall strength of the conclusions drawn in this review. Lastly, this literature review paper focused solely on the diagnostic aspect of oral cancer using artificial intelligence.

The purpose of this survey study is to examine the present environment and attitudes towards the application of artificial intelligence in the detection of oral cancer. The authors seek to determine the present difficulties, prospective advantages, and future possibilities for integrating artificial intelligence technology in the field of diagnosing oral cancer by gathering information from the literature. This research paper's main goal is to look into how AI tools and algorithms are currently being used and applied in the diagnosis of oral cancer. To examine the algorithms or models now in use for diagnosing oral cancer, comprehend the reasoning behind the algorithmic results, and to offer suggestions for future work and the creation of AI-based systems for better oral cancer diagnosis. By achieving these goals, this survey study hopes to make a significant contribution to the field of artificial intelligence-based oral cancer diagnosis.

The paper begins with the introduction, where the research problem and its significance are presented. Section 2 represents the literature review which is divided into 2 subsections one is Study Selection and other one is Data capture and synthesis. Section 3 of the paper focuses on results and analysis. Section 4 is a discussion and in section 5 conclusion and features are explained.

2. Literature Review

The goal of the literature review section of this paper on artificial intelligence-assisted oral cancer diagnosis is to examine the body of knowledge already available in this area. We have investigated the various techniques, methodologies, and developments in the application of artificial intelligence for identifying and diagnosing oral cancer by conducting an extensive evaluation of published papers. The main conclusions and contributions of earlier research is covered in detail in this section. By combining and evaluating the existing research, we have tried to lay down the groundwork for investigation and pinpoint areas in which more investigation is necessary to improve the efficacy and accuracy of artificial intelligence-based oral cancer diagnostics. Relevant keywords encompassing oral cancer, diagnosis, detection, etc. were covered in this study. The research study of B. Song et al [1] provided a comprehensive overview of the past, present, and future of oral cancer screening. Their study discusses the historical context of oral cancer screening methods, their limitations, and the advancements made in recent years. The authors examined advanced technologies and techniques, such as molecular markers, imaging technologies, and artificial intelligence, to assess their potential to enhance oral cancer screening. They emphasized the importance of early detection and highlighted the challenges involved in implementing successful screening programs. The authors concluded that there is a need for further research and collaboration to develop more accurate and accessible screening methods for oral cancer. The research study conducted by Seoane J et al. [2] is a systematic review with meta-analysis to investigate the impact of delay in diagnosis on the survival of patients with head and neck carcinomas. The study analyzed multiple research articles on the topic and synthesized the data to draw conclusions. The study's findings indicated that a longer delay in discovering the presence of malignancies of the head and neck contributed to decreased survival results. This implies that early detection and prompt diagnosis play a crucial role in improving the prognosis and survival of patients with these types of cancers. Gigliotti et al. [3] examine the factors contributing to the delay in the detection of oral cancer and their impact on the outcomes of patients. Through an analysis of patient data, the study revealed that delays in oral cavity cancer diagnosis are prevalent and often result from patient-related factors, healthcare system-related factors, and tumor-related factors. To boost the prognosis and survival rates for patients with oral cavity cancer, the study underlined the significance of early detection and timely treatment. In their investigation study, a smartphone-based, point-of-care, dual-modality, dual-view oral cancer screening tool designed for underdeveloped areas was presented by Uthoff et al. [4]. The device combines visual and fluorescence imaging techniques to capture oral cavity images, which are analyzed using a neural network classification system. The study demonstrated the feasibility and effectiveness of the device in detecting oral cancer and precancerous lesions. The device provides a cost-effective and accessible screening tool that has the potential to improve early detection and management of oral cancer in resource-limited settings. In their research, an improved computational model for detecting oral cancer was presented by Al-Ma'aitah and AlZubi [5]. The accuracy and efficiency of the detection process were focused on being enhanced by combining gravitational search optimization with echo state neural networks. The aim was to optimize the performance of the neural network model for more effective oral cancer detection. The proposed model is evaluated using oral cancer datasets, and the results demonstrate its effectiveness in accurately detecting oral cancer. The study suggested that the enhanced computational model has the potential to assist in early diagnosis and improve the outcomes of oral cancer treatment. Turki and Wei [6] proposed a method utilizing support vector machines (SVMs) for cancer classification and detection. The researchers proposed a boosting framework that combines multiple SVM classifiers to improve accuracy and overcome the limitations of individual SVMs. The proposed method is evaluated using various cancer datasets, and the results demonstrate its effectiveness in achieving higher classification accuracy compared to traditional SVMs. The findings of the study indicated that the implementation of the boosting approach has the potential to enhance cancer detection, offering valuable support in the diagnosis and treatment of cancer. Cheng et al. [7] proposed a reliable and accurate model that can identify the risk factors associated with the recurrence of oral cancer i.e. Evidence-based diagnostic model for predicting recurrence risk factors of oral cancer. By employing statistical tools, the researchers conducted an analysis of a dataset comprising oral cancer patients to identify the crucial factors associated with recurrence. Based on these predictors, they proposed a recurrence risk prediction model. The results of the study demonstrated the effectiveness of the adapted model in accurately predicting the risk factors for the recurrence of oral cancer. The proposed model can be used as a valuable tool in guiding clinical decision-making and improving the management of oral cancer patients. D. K. Das et al. [8] conducted a research study that centered on automating the identification of diagnostically significant regions from histological images of oral tissue to diagnose oral squamous cell carcinoma (OSCC). The researchers developed a computer-aided system that can assist in accurately detecting and analyzing specific regions in histological images that are indicative of OSCC. The study proposed a methodology that combines image processing techniques and machine learning algorithms to automatically identify these clinically relevant regions. In their study, a novel approach utilizing deep learning techniques for the automated classification of oral dysplasia and malignancy images acquired through dual-modality smartphone imaging was presented by B. Song et al. [9]. The researchers aimed to develop a computer-based system that can accurately classify oral images acquired from a smartphone into dysplasia and malignancy categories. The proposed method employed deep learning algorithms to extract meaningful features from the images and trained a classification model to differentiate between different pathology classes. The research study of J. Folmsbee et al. [10] proposed a method called "active deep learning" that selects and labels the most informative samples during the training process to enhance the network's performance. The research study revealed strong support for the active deep learning approach's ability to improve convolutional neural networks' (CNNs') training efficiency for categorizing oral cavity cancer tissue. The outcomes highlighted the approach's potential to considerably raise the precision and effectiveness of deep learning models while examining medical images, especially when dealing with the setting of cancer of the oral cavity. The development and deployment of a computer-based system that makes use of MATLAB as a tool to aid in the identification of oral cancer was suggested in the research paper by N. Kripa et al. [11]. The system is designed to analyze oral images or data and provide diagnostic support to healthcare professionals. In the research study conducted by A. Nawandhar et al. [12], machine learning techniques combined with neighborhood feature selection were employed to develop a classifier specifically for stratified squamous epithelial biopsy images. The study proposed a method that combines machine learning techniques with a feature selection approach based on neighborhood information to accurately classify biopsy images. H. Yan et al. [13] proposed a methodology on the discrimination of tongue squamous cell carcinoma using Raman spectroscopy and convolutional neural networks (CNN). The study utilizes Raman spectroscopy as a non-invasive technique to analyze the molecular composition of tissues and identify cancerous cells in tongue samples. The researchers then employ CNN, a deep learning algorithm, to develop a classification model that can accurately distinguish between normal and cancerous tongue tissues based on the Raman spectroscopy data. The categorization of tongue squamous cell carcinoma utilizing tongue samples was the subject of a study conducted by M. Yu et al. [14]. To accomplish accurate and effective disease categorization, the study combined Raman spectroscopy with deep convolutional neural networks (CNN). A unique deep learning architecture was employed by C.H. Chan et al. [15] in their research study to enhance the accuracy of oral cancer detection. Their approach involved the development of a texture-map-based branch-collaborative network, which effectively incorporated texture map information to improve the identification of oral cancer. Multiple branches are included in the proposed network to extract features from different regions of the oral cavity images, and accurate predictions are collaboratively learned. In the study by A.M. Bur et al. [16], machine learning approaches were used to forecast the occurrence of occult nodal metastases in early-stage oral squamous cell cancer (OSCC). The main goal of the study was to examine whether patients diagnosed with early-stage OSCC had concealed lymph node metastases using these methods. A potential tool is provided by the study through the development of a predictive model that can accurately identify the presence of nodal metastasis in patients with early-stage OSCC. For the purpose of diagnosing oral cancer on samples of salivary exosomes, A. Zlotogorski-Hurvitz et al.'s research study [17] combined Fourier transform infrared (FTIR) spectroscopy with computationally assisted discriminating analysis. Different supervised machine learning classification algorithms for predicting locoregional recurrences in early oral tongue cancer were compared by R. O. Alabi et al. [18] in their study. The clinical and histological characteristics of patients with oral tongue cancer were used by the researchers to assess the efficacy of different supervised machine learning algorithms using the metrics accuracy, sensitivity, specificity, and area under the curve (AUC). The outcomes showed that in early oral tongue cancer patients, the SVM algorithm outperformed other classification techniques in predicting locoregional recurrences. R. O. Alabi et al. [19] proposed a web-based prognostic tool utilizing machine learning for predicting locoregional recurrences in early oral tongue cancer to assist clinicians in making informed decisions regarding treatment strategies and patient management. The authors examined the performance in terms of accuracy, sensitivity, specificity, and area under the curve (AUC) using clinical and histological characteristics of patients with early oral tongue cancer. A deep neural-based adaptive fuzzy logic system was proposed by K. Lalithamani and A. Punitha [20] as a system for the identification of oral cancer. A dataset comprising oral cancer-related features was used by the authors, and a deep neural network was employed for feature extraction and classification. Fuzzy logic was also applied to adaptively adjust the membership function parameters based on the input data. The performance of the proposed system is evaluated in terms of accuracy, sensitivity, specificity, and F1 score. L. Lavanya and J. Chandra [21] conducted a research study to investigate the capabilities of machine learning algorithms in detecting and classifying oral cancer. The potential of these algorithms in accurately identifying and categorizing oral cancer cases was sought to be assessed by the study. The researchers applied various machine learning algorithms, such as decision trees, random forests, support vector machines, and k-nearest neighbors, for analysis and classification. The research paper by O. A. Karadaghy et al. [22] presented a model that enhances prognostic predictions and aid in treatment decision-making for OSCC patients by utilizing machine learning algorithms. A large cohort of OSCC patients was used to train and validate the predictive model, which incorporated patient characteristics and clinical variables. Research was conducted by S. Sunny et al. [23] that focused on the development of a point-of-care platform for oral cancer screening using smart tele-cytology. The study aimed to create an innovative and convenient system that enables oral cancer screening through remote cytology, enhancing accessibility and convenience for patients. The developed platform utilizes a smartphone-based system that captures and transmits cytology images of oral lesions to remote pathologists for analysis. Machine learning algorithms were employed to assist in the classification and identification of cancerous cells. An early diagnostic technique for oral cancer using computer-assisted medical image categorization was presented in the study by P. R. Jeyaraj and E. R. Samuel Nadar [24]. A deep learning algorithm was utilized in the study to analyze medical images and accurately classify oral lesions as cancerous or non-cancerous. Y. Ariji et al. [25] employed a deep learning artificial intelligence (AI) system to analyze contrast-enhanced computed tomography (CT) images to detect cervical lymph node metastases in patients diagnosed with oral cancer. The study demonstrated the potential of utilizing advanced AI technologies to aid in the identification of lymph node involvement, offering valuable insights for accurate staging and treatment planning in oral cancer patients. The study aimed to evaluate the accuracy and reliability of the AI system in detecting lymph node metastasis, an important factor for staging and treatment planning in oral cancer patients. The AI system was trained on a dataset of contrast-enhanced CT images and learned to identify and classify metastatic lymph nodes. The performance of the system was assessed by comparing its results with those of experienced radiologists. In the study conducted by S. Xu et al. [26], a novel approach for the early diagnosis of oral cancer was developed using three-dimensional convolutional neural networks (CNNs). The power of deep learning algorithms was harnessed to enhance the accuracy and efficacy of oral cancer diagnosis, aiming to offer a promising method for timely detection and improved patient outcomes. The proposed method involved training CNNs on a dataset of three-dimensional images of oral lesions. The trained models were then used to classify new images and identify potential cancerous regions. In order to identify oral cavity squamous cell cancer (OCSCC) from photographic pictures, the study introduced the application of a deep learning system in endoscopy for the detection of early esophageal squamous cell carcinoma (ESCC) by S. L. Cai et al. [27]. A deep learning system was introduced by Q. Fu et al. [28]. The algorithm was trained on a retrospective dataset of photographic images of the oral cavity, which included both normal and cancerous cases. The research paper by V. Romeo et al. [29] presented a model for predicting tumor grade and nodal status in oropharyngeal and oral cavity squamous-cell carcinoma (SCC) using a radiomic approach. The study aimed to improve the accuracy of tumor grading and nodal status assessment by leveraging radiomic features extracted from medical imaging data. A point-of-care oral cytology instrument developed and evaluated by M. P. McRae et al. [30] was made specifically for the screening and assessment of potentially cancerous oral lesions. The tool employed a simple and non-invasive device to collect oral cytology samples, which were subsequently subjected to a combination of cytological examination and image analysis techniques. To identify occult lymph node metastasis in oral squamous cell carcinoma (OSCC), a technique to verify a multivariable prediction model was devised by M. Mermod et al. [31]. The purpose of the study was to improve the predictive model's ability to accurately identify lymph node metastasis by including a variety of clinical and histological criteria. The accuracy of detecting lymph node metastases in OSCC patients has the potential to be increased by this strategy. To enable early identification of oral cancer, R. A. Welikala et al. [32] introduced an automated method for the detection and classification of oral lesions. The goal of the study was to employ deep learning algorithms to increase the efficiency and accuracy of diagnosing oral cancer. The system was trained on a large dataset of oral images and learned to identify and classify different types of oral lesions. A deep learning neural network for texture feature extraction in oral cancer, with a specific focus on enhanced loss function, was introduced in the research paper by R. B. Bhandari et al. [33]. The neural network was trained on a dataset of oral cancer images, and meaningful texture features associated with oral cancer were learned. The authors optimized the network's performance by incorporating additional information during training through the enhanced loss function. P. R. Jeyaraj et al. [34] presented a deep learning-based approach for the non-invasive detection of oral cancer from hyperspectral images by fusing classifier features. A deep learning model was trained on a dataset of hyperspectral images, and classifier features were extracted as part of the proposed approach. To improve the effectiveness of the model in detecting oral cancer, these features were then combined using a fusion technique. In the research paper by R. Prabhakaran and Dr. J. Mohana, [35] the focus was on detecting oral cancer using machine learning classification methods. The objective was to enhance the accuracy and efficiency of oral cancer detection by utilizing the capabilities of machine learning algorithms. A dataset of oral cancer cases was collected, and various machine-learning classification methods were employed to develop models for detecting oral cancer. To improve the precision and effectiveness of oral cancer diagnosis, K. Warin et al. [36] carried out a study on the automatic categorization and detection of oral cancer in photographic pictures using deep learning algorithms. The researchers developed and trained deep learning algorithms using a dataset comprising photographic images of oral lesions, enabling the algorithms to classify and detect oral cancer. F. Jubair et al. [37] unveiled a newly developed lightweight deep convolutional neural network (CNN) in their research paper, aiming to enhance early detection of oral cancer. The study aimed to improve the efficiency and accuracy of oral cancer diagnosis by utilizing a specialized CNN architecture. The researchers developed the lightweight CNN model specifically designed for oral cancer detection, considering the computational constraints of resource-limited devices. The research conducted by G. Tanriver et al. [38] aimed to utilize deep learning techniques for automating the detection and classification of oral lesions, with the ultimate goal of identifying oral potentially malignant disorders (OPMDs). The researchers developed a deep learning-based system that examined oral lesion images and autonomously recognized and categorized OPMDs. Automatic oral cancer identification in smartphone-based photos using deep learning algorithms for early diagnosis was the focus of a study by H. Lin et al. [39]. A deep learning model was developed by the researchers to analyze oral images captured with smartphones and automatically identify signs of oral cancer. The research paper by S. Camalan et al [40] focused on the development of clinical predictors for oral dysplasia using convolutional neural network (CNN) models. By analyzing the class activation maps, the researchers identified the relevant regions and important features associated with oral dysplasia. In the research study, an ensemble deep neural network approach for oral cancer screening was presented by N. B R et al. [41]. An ensemble model was constructed by combining multiple deep neural networks to improve the screening performance. The effectiveness of the approach was evaluated using various metrics, and it was observed that the ensemble deep neural network outperformed other methods in oral cancer screening. The utilization of deep learning techniques for the automatic segmentation of oral and oropharyngeal cancer using narrow band imaging was explored in the research paper by A. Paderno et al. [42]. A deep learning model was developed to analyze narrow band imaging data and automatically identify and delineate cancerous regions within the oral and oropharyngeal areas. The creation of DEEPORCD, a deep learning system specifically designed for oral cancer detection, was the focus of the research conducted by Dharani R and Revathy S [43]. The DEEPORCD model, employing deep learning algorithms to analyze oral images and identify regions affected by cancerous growth, was successfully developed by the researchers. In their study, a tool that aids in the point-of-care classification of oral cancer using a mobile platform was introduced by B. Song et al. [44]. A mobile application was developed and implemented by the authors, utilizing machine learning algorithms to analyze oral images and classify them as cancerous or non-cancerous. The research study conducted by Disha et al. [45] presented a deep learning algorithm utilizing convolutional neural networks (CNN) to identify and differentiate oral precancerous and cancerous lesions from normal mucosa. The CNN model was trained on a large dataset of oral lesion images, and its ability to accurately classify lesions as precancerous or cancerous and distinguish them from normal mucosa was evaluated. In a study published in [46], the possibility of artificial intelligence (AI)-driven interpretation of optical coherence tomography (OCT) images used for oral cancer screening was explored by K. Ramezani and M. Tofangchiha. The feasibility of using AI algorithms to analyze OCT images to detect and diagnose oral cancer was investigated in the study. The researchers developed an AI-based system that analyzed OCT images and provided accurate evaluations of oral cancer presence.

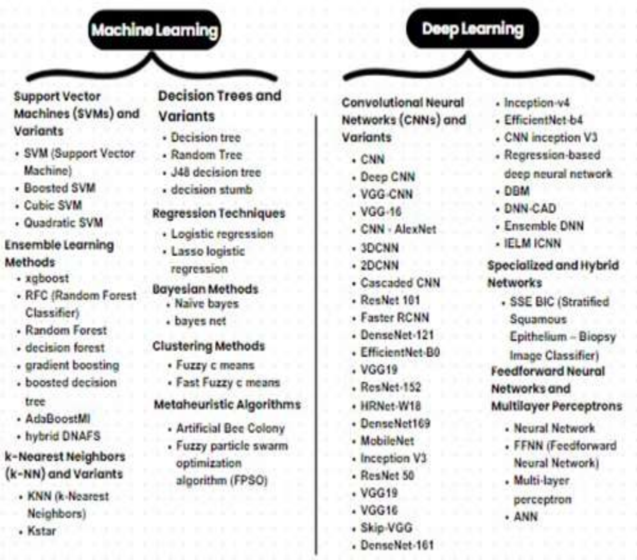

Figure 1. *AI, Ml, Dl Methods Used in the Studies*

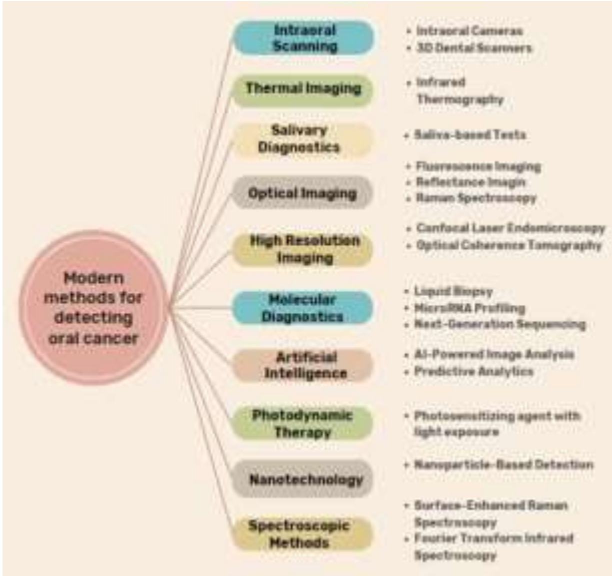

Figure 2. *Key Sites and their Cancer Types*

Figure 1 shows AI, Ml, Dl methods used in the studies. All the findings highlighted its potential as a valuable tool for oral cancer screening. These works pushed the field forward by presenting an AI-focused method for interpreting several imaging modalities, opening up intriguing possibilities to improve oral cancer early detection and diagnosis. Oral cancer primarily affects several key regions within the oral cavity, each with its specific cancer varieties. These regions and their respective cancer varieties are depicted in Figure 2.

The most prevalent form of oral cancer is squamous cell carcinoma (SCC), which frequently impacts the lips, particularly the lower lip. SCC and verrucous carcinoma, a slower-growing variant, can both develop on the tongue, another significant site. Adenocarcinoma and mucoepidermoid carcinoma, both of which originate from salivary gland tissues, are both capable of affecting the floor of the mouth. SCC can also develop in the buccal mucosa, which is the inner cheek lining. Minor salivary gland malignancies, including adenoid cystic carcinoma, can impact the hard palate, which is the roof of the mouth. Predominantly SCC, and gingival (gum) malignancies affect the tissues that encircle the teeth. SCC or other rarer forms, such as odontogenic carcinoma, can develop in the retromolar trigone, the region behind the last molars. The significance of comprehensive examination and targeted diagnostic methods for effective early detection and treatment is emphasized by the susceptibility of each region to distinct types of malignancies.

The diagnostic landscape has been transformed by contemporary methods of oral cancer detection, which have enabled the early and precise identification of malignancies. These methods capitalize on technological innovations to offer non-invasive, precise, and swift diagnostics. Intraoral scanning is a technique that employs high-resolution optical devices to acquire detailed 3D images of the oral cavity, thereby enabling the early detection of precancerous lesions.

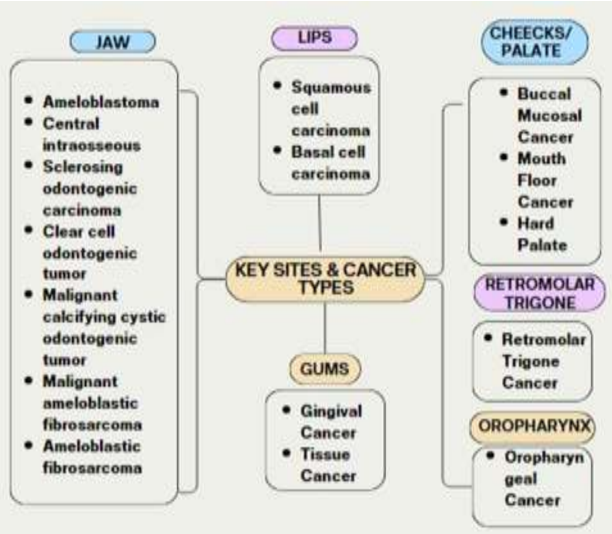

Figure 3. *Modern Methods for Detection of Oral Cancer*

Optical Coherence Tomography (OCT) and confocal laser endomicroscopy (CLE) are high-resolution imaging techniques that provide microscopic views of cellular architecture and tissue structures, respectively.

This enables the differentiation between benign and malignant tissues. Liquid biopsy, a non-invasive technique, detects cancer-related genetic material in bodily secretions such as saliva and blood. This method offers a less invasive alternative to traditional biopsy methods and allows for the continuous monitoring of disease progression. Comprehensive genetic analysis is facilitated by next-generation sequencing (NGS), which identifies novel mutations and potential therapeutic targets.

Through predictive modeling and automated image analysis, the integration of machine learning (ML) and artificial intelligence (AI) improves diagnostic accuracy. Furthermore, the precision of treatment and the visualization of lesions are enhanced by fluorescence imaging and photodynamic therapy (PDT). The promotion of earlier detection, personalized treatment, and improved patient outcomes is the result of the significant strides made in the fight against oral cancer by these modern methods. Figure 3 shows the modern methods for the detection of oral cancer.

A. Study Selection

Studies that employed artificial intelligence, deep learning, machine learning, and image analysis to aid in the detection of oral cancer were the primary inclusion criteria. There were no restrictions on the categories of technologies or imaging modalities that were included. A wide range of investigations, such as those employing AI/ML to detect or distinguish between benign, pre-malignant, and malignant pathology, is needed due to the projected dearth of studies in the field. First, all publications were examined to check the study title, and abstract, and to weed out any duplicates. The second screening step involved a comprehensive full-text examination against the predefined criteria.

B. Data Capture And Synthesis

The data was deduced and decoded in the appropriate formats for further analysis and examination. The extracted information encompasses the publication year, dataset size, algorithms examined, overall aim, objectives, performance metrics employed, limitations of the study, and conclusions. The Discussion section provides a comprehensive summary of the information, and tables and charts are used to display the data.

3. Result and Analysis

Post-comprehensive evaluation, 50 studies were considered for further examination. Below is a chronological split of these studies shown in Table 1.

Table 1: *Chronological Split of Studies*

Count	Year of Publications
7	2018
15	2019
10	2020
8	2021
3	2022
4	2023

The areas were focused on techniques used, performance metrics, imaging modality, and data size. A multitude of modalities were incorporated for the training and optimization of algorithms. These included auto-fluorescence imaging (AFI) and white light imaging (WLI), clinical photographs, tissue slide images, microscopic images, cell images, auto-fluorescence images, high-resolution cytology images, CAT scan images, esophageal images, MRI scans, hyperspectral image data, and optical coherence tomography images. This distribution is represented in Figure 4.

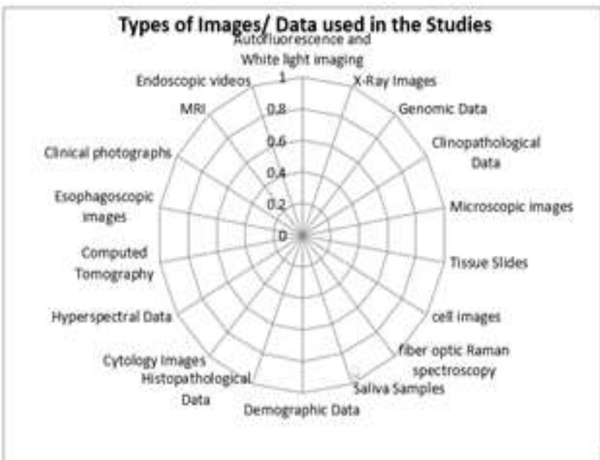

Figure 4. *Type of images/ data used in the studies*

White light imaging and auto-fluoresce imaging were utilized in 4 investigations to diagnose oral cancer. One of these [1, 2] created a smartphone-based, dual-view, point-of-care oral cancer screening system for high-risk groups that uses white light imaging (WLI) and auto-fluorescence imaging (AFI). As a result, precancerous and cancerous lesions in the oral cavity can be found early, potentially lowering mortality, morbidity, and overall healthcare expenses.

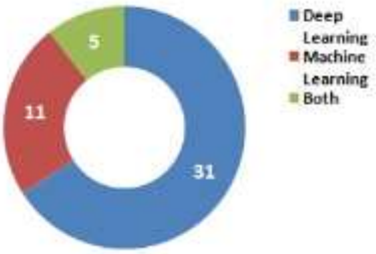

Figure 5. *Types of Methods Used*

These image pairings were of high enough quality to be used in the CNN and for remote diagnosis [2]. Figure 5 depicts the Percentage of Artificial Intelligence methods used. Conventional Machine Learning methods were deployed in ten studies, Deep Learning techniques were used in thirty studies and an amalgamation of both were used in 3 studies. It is important to provide a brief overview that places the findings within the larger study environment, and Table 2 does just that by showcasing the conclusions drawn from a wide range of literature studies. Analyzing these publications in-depth reveals that applying cutting-edge AI methods to difficult situations has yielded encouraging outcomes. Constant research and new developments in the subject are reflected in the wide variety of methodologies. These include everything from algorithmic methods for deep learning to reinforcement learning techniques. The necessity of large-scale and diversified samples for sustainable model performance has also been underlined through the evaluation of distinct datasets and image formats. Accuracy, precision, recall, and the F1- score are some of the most popular metrics used to assess performance, but these criteria are not universally applied across research. Together, these results highlight the need for constant advancement and research in artificial intelligence to expand the scope and usefulness of the field. The diagnosis of oral cancer has been greatly aided by the development of AI. Many studies have looked into the possibility of using AI-based systems to enhance the precision, speed, and early detection of oral cancer. The following table 2 summarizes the most important takeaways from these studies, illuminating the tremendous strides made in utilizing AI for oral cancer diagnosis. The performance metrics with respect to the aforementioned research works across the different algorithms are presented year-wise in figures 6-10.

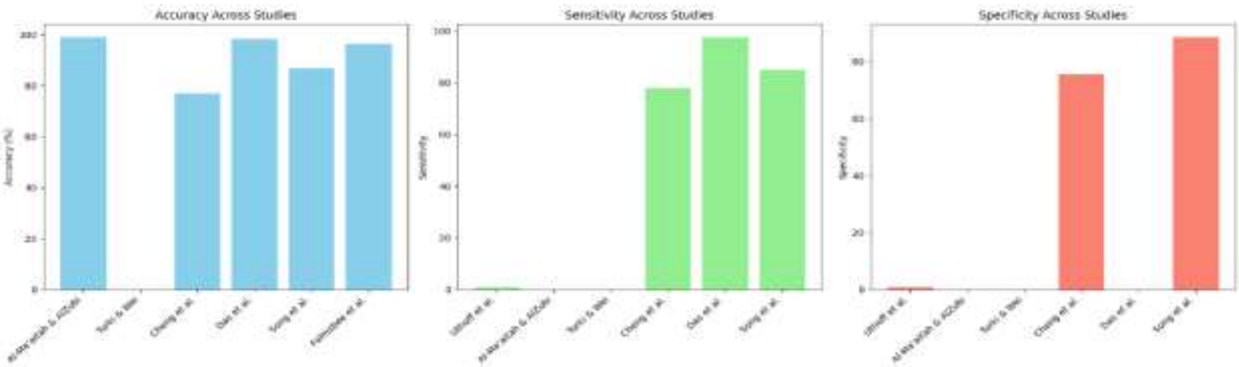

Figure 6. *Performance Metrics 2018*

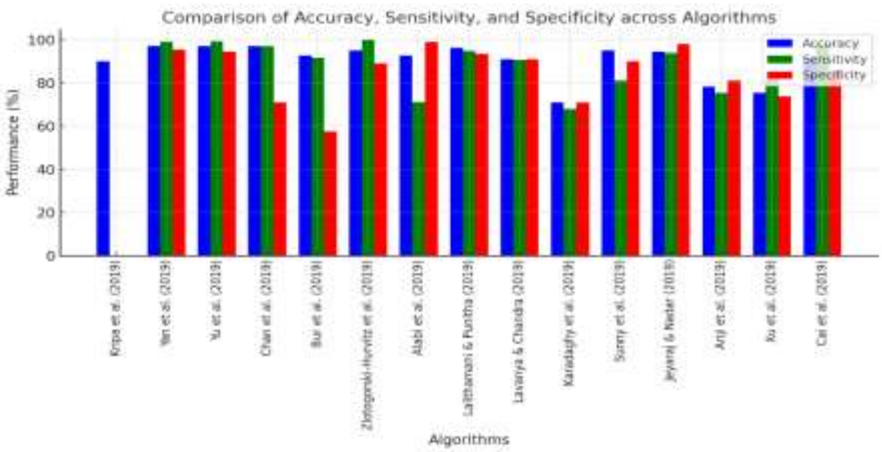

***Figure 7**. Performance Metrics_2019*

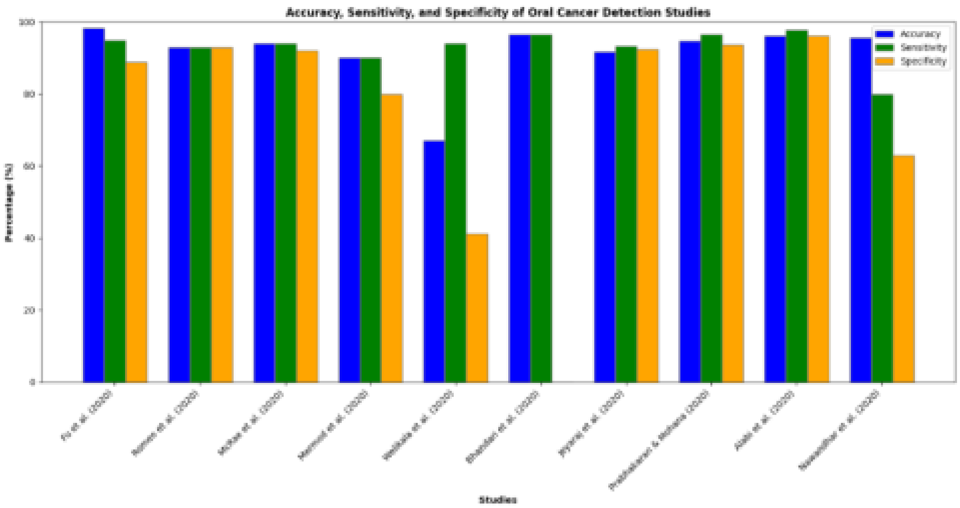

Figure 8. *Performance Metrics 2020*

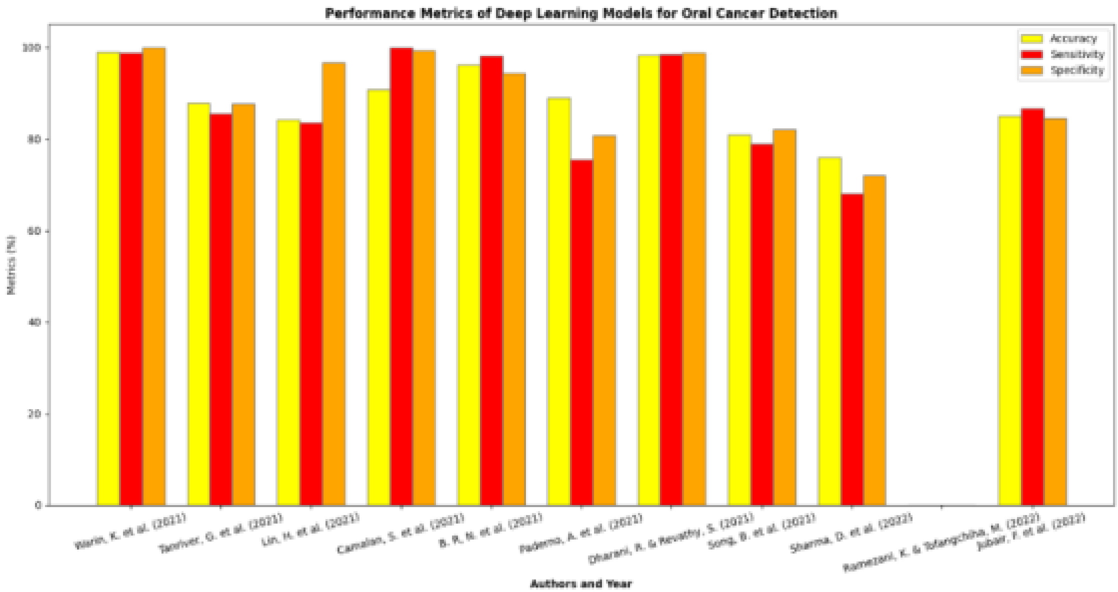

Figure 9. *Performance Metrics 2021 & 2022*

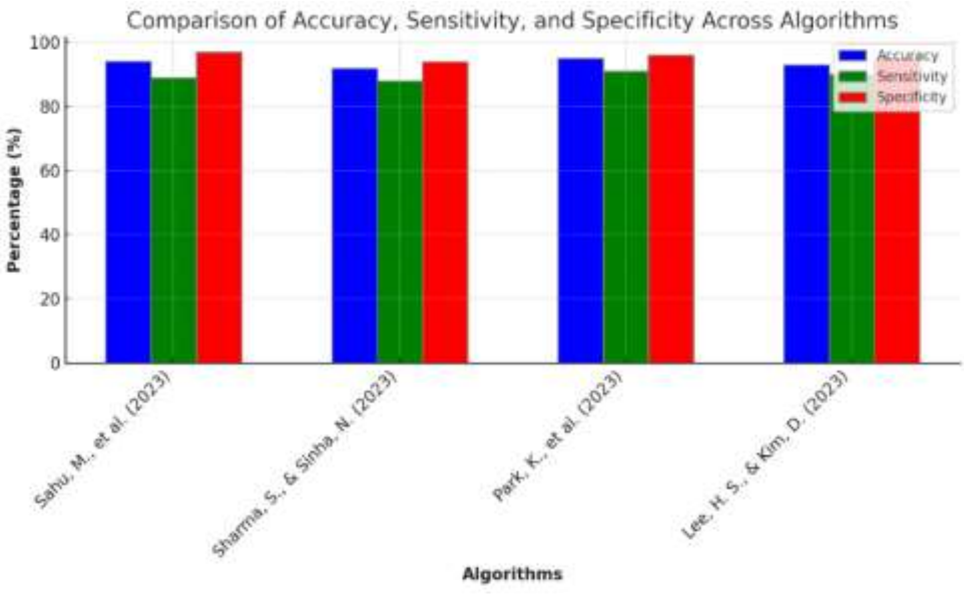

Figure 10. *Performance Metrics 2023*

Table 2. *Conclusion Drawn by Various Studies*

Paper	Conclusion/ Key Takeaways
Uthoff, R. D., et al. (2018) [4]	As per the findings of the study, a screening device for oral cancer that utilizes neural network classification, dual-modality, and dual-view imaging features and is based on smartphones has been deemed appropriate for implementation in areas with limited resources.
Al-Ma'aitah, M., &AlZubi, A. A. (2018). [5]	The research paper concluded that the proposed computational model, which combined gravitational search optimization (GSO) with echo state neural networks (ESNs), showed promise for oral cancer detection.
Turki, T., & Wei, Z. (2018) [6]	According to the study's findings, applying boosting techniques can greatly improve how well support vector machines (SVMs) perform when used for tasks like cancer classification. The findings demonstrated that the boosted SVM models achieved superior accuracy and exhibited enhanced discrimination capabilities in comparison to standalone SVMs.
Cheng, C. S., et al. (2018) [7]	The research paper concluded that adapting an evidence-based diagnostic model can be useful in predicting the risk factors for recurrence in oral cancer. By analyzing various clinical and pathological factors, the adapted diagnostic model demonstrated its effectiveness in predicting the recurrence risk in oral cancer patients.
Das, D. K., et al. (2018) [8]	The study found that finding clinically significant regions from oral tissue histological images using automated methods and advanced image processing techniques increases the precision and effectiveness of OSCC diagnosis.
Song, B., et al. (2018) [9]	The research study concluded with the successful implementation of an automated classification system using deep learning techniques to distinguish between oral dysplasia and malignancy in dual-modality smartphone-based images. The researchers found that their deep learning model effectively analyzed the dual-modality images and accurately classified them into dysplastic or malignant categories.
Folmsbee, J., et al. (2018)[10]	The research study demonstrated the effective use of active deep-learning techniques to raise CNNs' capacity for tissue classification training. The researchers found that by incorporating active learning strategies, such as querying the most informative samples during the training process, the CNN model achieved better classification performance with fewer labeled training samples.
Kripa, N., et al. (2019) [11]	The conclusion was the successful design and implementation of the DSS for oral cancer detection. The researchers developed a system that leveraged MATLAB's capabilities to analyze oral images and extract relevant features for classification. The DSS demonstrated promising results in accurately detecting oral cancer, providing valuable support to healthcare professionals in making diagnostic decisions.
Nawandhar, A., et al. (2020) [12]	The conclusion was the successful implementation of the image classifier for stratified squamous epithelial biopsy images. The researchers utilized machine learning algorithms and feature selection methods based on the neighborhood characteristics of the image pixels. The classifier demonstrated promising accuracy and performance in distinguishing between different classes of stratified squamous epithelial biopsy images.
Yan, H., et al. (2019) [13]	The conclusion of the research paper was the successful application of Raman spectroscopy combined with CNNs for the discrimination of TSCC. The researchers concluded that Raman spectroscopy, when analyzing the molecular composition of tissues, in combination with CNNs, achieved high accuracy in distinguishing between normal and cancerous tongue tissue samples.
Yu, M., et al. (2019) [14]	The researchers concluded that the application of deep CNNs accurately classified TSCC based on Raman spectroscopy data. The researchers showed that the deep CNN model effectively learned and extracted meaningful features from the Raman spectroscopy signals, leading to high accuracy in differentiating between normal and cancerous tongue tissue samples.
Chan, C. H., et al. (2019) [15]	The conclusion of the research paper proposed the development of a collaborative network for oral cancer diagnosis that utilized texture maps and collaborative learning techniques. This network was designed to capture the intricate details of oral images and enhance the accuracy of the diagnosis. The network that utilizes texture mapping and collaborative branching exhibited encouraging outcomes in precisely detecting instances of oral cancer.
Bur, A. M., et al. (2019) [16]	Machine learning methods successfully predicted early-stage OSCC nodal metastases. Their clinical and histological data-trained machine learning model accurately identified patients at risk of covert nodal metastases.
Zlotogorski-Hurvitz, A., et al. (2019) [17]	The study's conclusion demonstrated how successfully FTIR-based spectrum analysis combined with computer methods may be used to diagnose oral cancer. The researchers proved that the FTIR spectroscopy of salivary exosomes, which captured molecular information, in conjunction with computational discrimination analysis, exhibited high accuracy in identifying people with oral cancer and those without it.
Alabi, R. O., et al. (2020) [18]	Different categorization techniques such as decision trees, random forests, support vector machines, and artificial neural networks were evaluated and ranked by the authors. The findings demonstrated that the accuracy and prediction capacities of these algorithms varied.
Alabi, R. O., et al. (2019) [19]	The authors successfully developed and implemented a prediction tool on the web that used machine learning methods on various clinical and histopathological patient features, successfully predicted cases of oral tongue cancer recurrence at a regional level in their earliest stages.
Lalithamani, K., &Punitha, A. (2019) [20]	For the identification of oral cancer, the authors proposed a technique wherein a deep neural network is combined with an adaptive fuzzy system. According to their findings, their system accurately detected and classified oral cancer based on the input data.This research proved the efficacy of combining data mining approaches with a deep neural network and an adaptive fuzzy system for better oral cancer detection and diagnosis.

Lavanya, L., & Chandra, J. (2019) [21]	At the end of the study, researchers stressed the need of using machine learning for assessing oral cancer. Based on a variety of clinical and histological markers, the researchers found that machine learning techniques such as decision trees, support vector machines, and random forests showed promising results in properly categorizing instances of oral cancer.
Karadaghy, O. A., et al. (2019) [22]	Researchers found that their efforts to create and test a machine learning model for predicting OSCC patients' survival rates were fruitful. The authors proved that their model, trained on clinical and demographic data, achieved a high level of accuracy in predicting patient survival rates. By considering various prognostic factors, the model provided valuable insights into the prognosis and outcome of OSCC.
Sunny, S., et al. (2019) [23]	Researchers created a smart oral cancer screening platform using tele-cytology. The system's integration of digital imaging, communication, and cytological analysis made it possible to screen for oral cancer lesions effectively and accurately. The platform facilitated real-time access to expert opinions and remote consultations, effectively overcoming geographical barriers and improving access to specialized care.
Jeyaraj, P. R., & Nadar, E. R. S. (2019) [24]	A deep learning algorithm was utilized to classify medical photos for early oral cancer detection. The system also accurately distinguished healthy and malignant oral tissue in medical photos.
Ariji, Y., et al. (2019) [25]	The study concluded that in oral cancer patients, the deep learning system accurately assessed cervical lymph node metastases. The deep learning algorithm detected and classified metastatic lymph nodes in contrast-enhanced CT images with excellent accuracy.
Xu, S., et al. (2019) [26]	The study revealed the efficacy of 3D CNNs in early identification of oral cancer. The researchers accurately diagnosed oral cancer lesions using 3D CNNs to analyze CT and MRI scans. The utilization of 3D CNNs enabled the extraction of relevant features and patterns from the three-dimensional image data, allowing for reliable classification of cancerous and non-cancerous tissues.
Cai, S. L., et al. (2019) [27]	The study concluded in emphasizing the effectiveness of the deep learning system in detecting early ESCC during endoscopic examinations. The researchers showed in their results that the deep learning system achieved high accuracy in identifying and classifying suspicious lesions in the esophagus, indicating the presence of early-stage ESCC.
Fu, Q., et al. (2020) [28]	Researchers showed that the deep learning approaches can accurately identify OCSCC from photographs. Their findings showed that deep learning has good sensitivity and specificity for distinguishing OCSCC lesions from normal oral cavity pictures.
Romeo, V., et al. (2020) [29]	The authors concluded that the radiomic approach results in SCC grade and nodal prediction.The findings showed that the radiomic features extracted from medical imaging data provided valuable information for characterizing tumor grade and identifying nodal involvement.
McRae, M. P., et al. (2020) [30]	To identify and assess potentially cancerous oral lesions, the authors developed and evaluated a point-of-care oral cytology instrument. They concluded by highlighting the effectiveness and potential utility of the oral cytology tool that provided accurate and reliable results, enables the detection of oral cancer-related cellular abnormalities.
Mermod, M., et al. (2020) [31]	An oral squamous cell carcinoma prediction model was developed and tested by the researchers to achieve their primary objective, which was to identify occult lymph node metastases. The authors incorporated various clinical and radiological factors to create the prediction model, which demonstrated good discrimination and calibration capabilities.
Welikala, R. A., et al. (2020) [32]	The researchers designed and validated a prediction model to detect concealed lymph node metastases in oral squamous cell carcinoma. The authors used a huge dataset of oral lesion photos to train the model, and they achieved great accuracy in lesion identification and classification tasks.
Bhandari, B., et al. (2020) [33]	The article concluded that an increased loss function improves neural network texture feature extraction. To train the neural network, the researchers utilized a large dataset consisting of oral cancer images, enabling the extraction of informative texture features. The incorporation of the enhanced loss function resulted in improved accuracy and increased robustness in capturing subtle textural variations associated with oral cancer.
Jeyaraj, P. R., et al. (2020) [34]	A deep learning algorithm for non-invasive oral cancer diagnosis was constructed using hyperspectral imagery. To do this, researchers used a deep learning framework and trained it using a dataset consisting of hyperspectral pictures of oral tissues. Classifier feature fusion boosts oral cancer detection deep learning model performance. The model's discriminatory power was improved by fusing features from several classifiers. The results demonstrated that the fusion of classifier features significantly enhanced the accuracy and reliability of oral cancer detection from hyperspectral images.
Prabhakaran, R., & Mohana, J. (2020) [35]	The authors showed the effectiveness of machine learning techniques in identifying and classifying cases of oral cancer. The researchers showed the performance on a dataset consisting of oral cancer images and applied various machine learning algorithms for classification, incorporating decision trees, k-nearest neighbours, and support vector machines. They ranked the algorithms based on their F1 score, accuracy, sensitivity, and specificity.
Warin, K., et al. (2021) [36]	In the publication, the authors demonstrated how, by creating a model powered by deep learning and training it on a dataset of oral cancer photos, deep learning techniques may be used to properly identify and categorize cases of oral cancer. To successfully identify between samples of normal as well as malignant oral tissue, the model showed good accuracy and performance.
Jubair, F., et al. (2022) [37]	For the purpose of early oral cancer diagnosis, the scientists created a lightweight deep convolutional neural network (CNN), and their strategy was geared towards overcoming the difficulty of implementing deep learning models in environments with limited resources. The lightweight CNN model that was developed achieved high accuracy in detecting oral cancer while utilizing a relatively small number of parameters. The model's low power requirements mean it can be used in portable gadgets like smartphones and edge devices.
Tanriver, G., et al.	The research study produced an automated system that accurately identified and categorizes oral lesions

(2021) [38]	using deep learning techniques. The study concluded with successful implementation of deep learning models that effectively detected and classified oral potentially malignant disorders.
Lin, H., et al. (2021) [39]	The research found that automated oral cancer screening from smartphone photographs could be improved with the help of deep learning algorithms. By training deep learning models on a diverse dataset of oral cancer images captured through smartphones, with a high degree of sensitivity and specificity, the researchers were able to correctly identify cases of oral cancer.
Camalan, S., et al. (2021) [40]	The study concluded that deep learning techniques were effectively applied for predicting oral dysplasia and identifying significant clinical predictors. To achieve this, the researchers trained a CNN model using a dataset of oral dysplasia images and conducted an analysis of the class activation maps enables the identification of specific regions of interest that have contributed to the predictions made by the model.
B. R, N., et al. (2021) [41]	The conclusion of the study highlighted the effectiveness of the proposed ensemble DNN model in accurately screening and detecting oral cancer. The scholars utilized a blend of several deep neural network models to enhance the general efficacy and dependability of the screening procedure. Through the process of combining the prognostications of said models, an elevated degree of precision and resilience was attained in the identification of oral cancer.
Paderno, A., et al. (2021) [42]	Narrow band imaging could be used to automatically segment oral and oropharyngeal malignancies using techniques based on deep learning, according to the findings of the research.The prelusive results demonstrated promising potential for clinical application, as the deep learning model achieved accurate segmentation of cancerous regions.
Dharani, R., &Revathy, S. (2021) [43]	The study's results showed that a Deep Learning model developed specifically for oral cancer detection was highly reliable.The model utilized deep learning techniques to analyze oral images and accurately identify cancerous lesions.
Song, B., et al. (2021) [44]	The research study concluded that a mobile-based oral cancer classification system could be effectively used for point-of-care screening. The system utilized mobile devices to capture oral images, and a classification algorithm based on deep learning techniques to analyze these images for the manifestation of oral cancer. The findings suggested that the mobile-based approach obtained a high degree of accuracy in the classification of oral lesions.
Sharma, D., et al. (2022) [45]	The findings of the research study indicated that the utilization of a deep learning algorithm based on a convolutional neural network was successful in identifying oral precancerous and cancerous lesions and distinguishing them from normal mucosa.
Ramezani, K., &Tofangchiha, M. (2022) [46]	The authors concluded that optical coherence tomography pictures interpreted with the help of artificial intelligence may be utilized to test for mouth cancer. In this work, OCT pictures of oral tissues were analyzed by artificial intelligence systems, and malignant and precancerous lesions were correctly diagnosed.

From the above figures, it is clear that the maximum accuracy measure obtained is 99.20 [5] and the lowest is 73.60 [40]. In the work of Al-Ma'aitah, M., &AlZubi, A. A. (2018). [5], The computational model is a combination of gravitational search optimization (GSO) with echo state neural networks (ESNs), which exhibits a promising accuracy percentage of oral cancer detection. Also, in Camalan et al. [40], deep learning techniques are used to predict oral cancer. This comparison between the maximum and minimum values of accuracy measures showcases the efficacy of the algorithms applied in cancer detection How AI has the potential to completely change how oral cancer is detected and treated is demonstrated by all of these findings together. Oral cancer management is set to undergo a radical shift as AI becomes increasingly crucial for improving diagnosis accuracy, patient outcomes, and overall practice.

4. Discussion

This draft gives a glimpse of AI methods application in the domain of diagnosing oral cancer. It has displayed an array of image ways utilized for algorithm training. Several studies point towards higher accuracy and precision that far exceed conventional techniques and human angle in predicting data. However limited machine learning tools have been exercised in practice.A bias analysis hasn't been conducted; the portrayed accuracy should be taken with caution. The primary reason is due to utilizing small data sets that could be biased. Multi-centric methods that cover a diverse array of records across the demography will augment algorithmic efficiency due to variance and diversity. Quick advancements in artificial intelligence and computing power have led to the development of numerous techniques for the quick detection of oral cancer. High-res. Digital methods have provided image extraction and conversion economically. Primitive work has been centered on conventional methods, but with the advent of deep learning – the diagnosis has evolved. This encourages the development of efficient deep-learning strategies used in conjunction with traditional methods to improve detection precision. The review has certain challenges as well. The primary constraint is the non-evaluation of integration between machine learning models. This could lead to the non-inference of optimum solutions.

5. Conclusion And Features

The use of AI in the diagnosis of oral cancer has advanced rapidly over a decade, becoming a game-changer in the medical industry. To better understand the substantial progress made and the possible impact on clinical practice, this survey article conducted a thorough analysis of the available literature and research projects that concentrated on the use of artificial intelligence in oral cancer diagnosis.

5.1 Conclusion

This article examines the prevalence, etiology, symptoms, and prevention of oral cancer. In addition, it highlights the potential significance of machine learning and deep learning models in oral cancer diagnosis. It is anticipated that the incorporation of artificial intelligence into early cancer detection will considerably improve clinical practices and outcomes. In addition, it provides excellent automation of numerous duties by analyzing complex patterns. Research plays a crucial role in facilitating this and also allowing for dynamic improvisation. The research studies discussed in this paper collectively demonstrate the advancements and potential of various techniques and technologies concerning the prevention, detection, and forecasting of oral cancer. The research conducted emphasizes the significance of timely detection and immediate intervention as crucial factors in enhancing patient outcomes and alleviating the impact of oral cancer. From the evolution of screening methods to the development of novel devices and computational models, these studies underscore the continuous efforts to enhance the accuracy, accessibility, and efficiency of oral cancer detection and management. Advancements in technology, such as the use of adjunctive tools like autofluorescence imaging, brush biopsy, salivary biomarkers, Raman spectroscopy, and Fourier-transform infrared spectroscopy, have contributed to improved screening and diagnostic capabilities. The amalgamation of aforementioned technologies, in conjunction with deep learning computational methods, neural networks with convolution, and machine learning techniques, has exhibited remarkable precision in identifying and categorizing oral cancer, thereby facilitating prompt diagnosis and treatment strategizing. These technologies offer non-invasive, cost-effective, and timely solutions for early detection, risk assessment, and treatment planning, leading to improved patient outcomes. These novel approaches can improve oral cancer management by increasing access to specialized care, eliminating geographical constraints, facilitating remote consultation, and optimizing clinical decision-making. Moreover, the integration of evidence-based diagnostic models and decision support systems has shown promising results in predicting recurrence risk factors and assisting clinicians in customized treatment strategies.

The research also emphasizes interdisciplinary teamwork and the promise of smartphone-based and low-cost devices for oral cancer screening, especially in marginalized regions. Furthermore, the emphasis on reducing diagnostic delays through awareness programs and efficient diagnostic strategies underscores the significance of early detection and timely intervention in oral cancer management. Overall, this research paper contributes to the growing body of knowledge with respect to oral cancer and reveals important details for researchers, clinicians, and policymakers. Future studies should focus on further validating these innovative approaches in diverse populations, integrating them into routine clinical workflows, and exploring their potential in personalized treatment approaches for oral cancer patients. Continued research and development in this area hold great promise for improving oral cancer outcomes, reducing mortality rates, and enhancing global healthcare accessibility.

5.2 Features

a) The utilization of machine learning algorithms for oral cancer diagnosis has dramatically decreased false-negative rates.
b) The diagnostic model powered by artificial intelligence has demonstrated an exceptional capacity to precisely categorize different stages and forms of oral cancer. This enhances the development of individualized treatment strategies and leads to a more favorable outlook for patients.
c) AI systems have shown the capacity to detect minor patterns and biomarkers that indicate the onset of oral cancer. Through the examination of extensive datasets, these technologies empower physicians to formulate more precise diagnostic judgments.
d) Integrating AI-based image processing tools with traditional diagnostic processes has greatly enhanced oral cancer screening. As a consequence, there has been a decrease in both the duration needed for diagnosis and the corresponding expenses.
e) AI-powered techniques for identifying oral cancer have demonstrated a significant degree of reliability and uniformity. This minimizes

differences in observations made by different individuals and improves the overall dependability of diagnostic results.

f) The utilization of artificial intelligence algorithms in combination with non-invasive imaging techniques has significant potential for enhancing the precision of early-stage oral cancer detection.

g) Although there have been significant breakthroughs, many AI models used for oral cancer diagnosis lack interpretability or explainability, sometimes operating as opaque "black boxes." This constraint presents challenges for the clinical adoption of AI models, as healthcare personnel must have a clear understanding of the decision-making process in order to trust the models and assure accurate diagnostic outcomes.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of 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
- **Acknowledgement:** I wish to convey my profound appreciation to my family for their steadfast support and encouragement during the duration of our study endeavor. I express profound gratitude to my mentor, Prof Sunil Kumar Khatri, for their essential mentorship, perceptive critique, and unwavering inspiration. Your proficiency and unwavering commitment have played a crucial role in the accomplished fulfillment of this task. I would like to express my heartfelt gratitude to my co-guide, Prof. Neeraj Kumar Sharma, for their valuable input, unwavering assistance, and extensive expertise, all of which played a crucial role in enhancing the quality and impact of this research.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] S. Warnakulasuriya, and A. R. Kerr, "Oral Cancer Screening: Past, Present, and Future," *Journal of Dental Research*, vol. 100, no. 12, pp. 1313–1320, 2021. https://doi.org/10.1177/00220345211014795

[2] J. Seoane, B. Takkouche, P. Varela-Centelles, L. Tomás, and J. M. Seoane-Romero, "Impact of delay in diagnosis on survival to head and neck carcinomas: A systematic review with meta-analysis," *Clinical Otolaryngology*, vol. 37, no. 2, pp. 99-106, 2012. https://doi.org/10.1111/j.1749-4486.2012.02464.x

[3] J. Gigliotti, S. Madathil, and N. Makhoul, "Delays in oral cavity cancer," *International Journal of Oral and Maxillofacial Surgery*, vol. 48, no. 9, pp. 1131-1137, 2019. https://doi.org/10.1016/j.ijom.2019.02.015

[4] R. D. Uthoff, B. Song, S. Sunny, S. Patrick, A. Suresh, T. Kolur, G, Keerthi, O. Spires, A. Anbarani, P. Wilder-Smith, M. A. Kuriakose, P. Birur, and R. Liang, "Point-of-care, smartphone-based, dual-modality, dual-view, oral cancer screening device with neural network classification for low-resource communities," *PLOS ONE*, vol. 13, no. 12, e0207493, 2018. https://doi.org/10.1371/journal.pone.0207493

[5] M. Al-Ma'aitah, and A. A. AlZubi, "An enhanced computational model for gravitational search optimized echo state neural networks based oral cancer detection," *Journal of Medical Systems*, vol. 42, no. 11, 205, 2018. https://doi.org/10.1007/s10916-018-1052-0

[6] T. Turki, and Z. Wei, "Boosting support vector machines for cancer discrimination tasks," *Computers in Biology and Medicine*, vol. 101, pp. 236-249, 2018. https://doi.org/10.1016/j.compbiomed.2018.08.006

[7] C. S. Cheng, P. W. Shueng, C. C. Chang, and C. W. Kuo, "Adapting an evidence-based diagnostic model for predicting recurrence risk factors of oral cancer," *Journal of Universal Computer Science*, vol. 24, no. 6, pp. 742-752, 2018. https://doi.org/10.3217/jucs-024-06-0742

[8] D. K. Das, S. Bose, A. K. Maiti, B. Mitra, G. Mukherjee, and P. K. Dutta, "Automatic identification of clinically relevant regions from oral tissue histological images for oral squamous cell carcinoma diagnosis," *Tissue & Cell*, vol. 53, pp. 111-119, 2018. https://doi.org/10.1016/j.tice.2018.06.004

[9] B. Song, S. Sunny, R. D. Uthoff, S. Patrick, A. Suresh, T. Kolur, G, Keerthi, A. Anbarani, P. Wilder-Smith, M. A. Kuriakose, P. Birur, J. J. Rodriguez, and R. Liang, "Automatic classification of dual-modality, smartphone-based oral dysplasia and malignancy images using deep learning," *Biomedical Optics Express*, vol. 9, no. 11, pp. 5318-5329, 2018. https://doi.org/10.1364%2FBOE.9.005318

[10] J. Folmsbee, X. Liu, M. Brandwein-Weber, and S. Doyle, "Active deep learning: Improved training efficiency of convolutional neural networks for tissue classification in oral cavity cancer," In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018). pp. 770-773, IEEE. https://doi.org/10.1109/ISBI.2018.8363686

[11] N. Kripa, R. Vasuki, and P. A. Surendhar, "Design of A Decision Support System for Detection of Oral Cancer Using MATLAB," vol. 8, no. 5, June 2019.

[12] A. Nawandhar, N. Kumar, R. Veena, and L. Yamujala, "Stratified squamous epithelial biopsy image classifier using machine learning and neighborhood feature selection," *Biomedical Signal Processing and Control*, 55, 2020, Art. no. 101671. https://doi.org/10.1016/j.bspc.2019.101671

[13] H. Yan, M. Yu, J. Xia, L. Zhu, T. Zhang, and Z. Zhu "Tongue squamous cell carcinoma discrimination with Raman spectroscopy and convolutional neural networks," *Vibrational Spectroscopy*, vol. 103, 2019, Art. no. 102938. https://doi.org/10.1016/j.vibspec.2019.102938

[14] M. Yu, H. Yan, J. Xia, L. Zhu, T. Zhang, Z. Zhu, X. Lou, G. Sun, and M. Dong, "Deep convolutional neural networks for tongue squamous cell carcinoma classification using Raman spectroscopy," *Photodiagnosis and Photodynamic Therapy*, vol. 26, pp. 430-435, 2019.

[15] C. H. Chan, T. T. Huang, C. Y. Chen, C. C. Lee, M. Y. Chan, and P. C. Chung, "Texture-Map-Based Branch-Collaborative Network for Oral Cancer Detection*," IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 4, pp. 766-780, 2019.

[16] A. M. Bur, A. Holcomb, S. Goodwin, J. Woodroof, O. Karadaghy, Y. Shnayder, K. Kakarala, J. Brant, and M. Shew, "Machine learning to predict occult nodal metastasis in early oral squamous cell carcinoma," *Oral Oncology*, vol. 92, pp. 20-25, 2019. https://doi.org/10.1016/j.oraloncology.2019.03.011

[17] A. Zlotogorski-Hurvitz, B. Z. Dekel, D. Malonek, R. Yahalom, and M. Vered, "FTIR-based spectrum of salivary exosomes coupled with computational-aided discriminating analysis in the diagnosis of oral cancer," *Journal of Cancer Research and Clinical Oncology*, vol. 145, no. 3, pp. 685-694, 2019. https://doi.org/10.1007/s00432-018-02827-6

[18] R. O. Alabi, M. Elmusrati, I. Sawazaki-Calone, L. P. Kowalski, C. Haglund, R. D. Coletta, A. A. Makitie, T. Salo, A. Almangush, and I. Leivo, "Comparison of supervised machine learning classification techniques in prediction of locoregional recurrences in early oral tongue cancer," *International Journal of Medical Informatics*, vol. 136, 2020, Art. no. 104068. https://doi.org/10.1016/j.ijmedinf.2019.104068

[19] R. O. Alabi, M. Elmusrati, I. Sawazaki-Calone, L. P. Kowalski, C. Haglund, R. D. Coletta, A. A. Makitie, T. Salo, I. Leivo, and A. Almangush, "Machine learning application for prediction of locoregional recurrences in early oral tongue cancer: A web-based prognostic tool*," VirchowsArchiv*, vol. 475, no. 4, pp. 489-497, 2019. https://doi.org/10.1007/s00428-019-02642-5

[20] K. Lalithamani, and A. Punitha, "Detection of oral cancer using deep neural based adaptive fuzzy system in data mining techniques," *International Journal of Recent Technology and Engineering*, vol. 7, pp. 397-405, 2019.

[21] L. Lavanya, and J. Chandra, "Oral cancer analysis using machine learning techniques," *International Journal of Engineering Research and Technology*, vol. 12, no. 5, pp. 596-601, 2019.

[22] O. A. Karadaghy, M. Shew, J. New, and A. M. Bur, "Development and assessment of a machine learning model to help predict survival among patients with oral squamous cell carcinoma," *JAMA Otolaryngology-Head & Neck Surgery*, vol. 145, no. 12, pp. 1115-1120, 2019. https://doi.org/10.1001/jamaoto.2019.0981

[23] S. Sunny, et al. "A smart tele-cytology point-of-care platform for oral cancer screening," *PLOS ONE*, vol. 14, no.11, 2019, Art. no. e0224885, https://doi.org/10.1371%2Fjournal.pone.0224885

[24] P. R. Jeyaraj, and E. R. S. Nadar, "Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm*," Journal of Cancer Research and Clinical Oncology*, vol. 145, no. 4, pp.829-837, 2019. https://doi.org/10.1007/s00432-018-02834-7

[25] Y. Ariji, M. Fukuda, Y. Kise, M. Nozowa, Y. Yanashita, H. Fujita, A. Katsumata, and E. Ariji, "Contrast-enhanced computed tomography image assessment of cervical lymph node metastasis in patients with oral cancer by using a deep learning system of artificial intelligence," *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology*, vol. 127, no. 5, pp. 458-463, 2019.

[26] S. Xu, C. Liu, Y. Zong, S. Chen, Y. Lu, L. Yang, E. Y. K. Ng, Y. Wang, Y. Wang, Y. Liu, W. Hu, C. Zhang, "An early diagnosis of oral Cancer based on three-dimensional convolutional neural networks," *IEEE Access*, vol. 7, pp. 158603-158611, 2019. https://doi.org/10.1109/ACCESS.2019.2950286

[27] S. L. Cai MD, B. L. MD, W. M. Tan, X. Niu, H. Yu MD, L. Yao MD, P. Zhou MD, B. Yan, and Y. Zhong MD, "Using a deep learning system in endoscopy for screening of early esophageal squamous cell carcinoma (with video)," *Gastrointestinal Endoscopy*, vol. 90, no. 5, pp. 745-753.e2, 2019. https://doi.org/10.1016/j.gie.2019.06.044

[28] Q. Fu, Y. Chen, Z. Li, Q. Jing, C. Hu, H. Liu, J. Bao, Y. Hong, T. Shi, K. Li, H. Zou, Y. Song, H. Wang, X. Wang, Y. Wang, J. Liu, H. Liu, S. Chen, R. Chen, M. Zhang, J. Zhao, J. Xiang, B. Liu, J. Jia, H. Wu, Y. Zhao, L. Win, and X. Xiong, "A deep learning algorithm for detection of oral cavity squamous cell carcinoma from photographic images: A retrospective study," *EClinicalMedicine*, vol. 27, Art. no. 100558, 2020. https://doi.org/10.1016%2Fj.eclinm.2020.100558

[29] V. Romeo, R. Cuocolo, C. Ricciardi, L. Ugga, S. Cocozza, F. Verde, A. Stanzione, V. Napolitano, D. Russo, G. Improta, A. Elefante, S. Staibano, and A. Brunetti "Prediction of tumor grade and nodal status in oropharyngeal and oral cavity squamous-cell carcinoma using a radiomic approach," *Anticancer Research*, vol. 40, no. 1, pp. 271-280, 2020. https://doi.org/10.21873/anticanres.13949

[30] M. P. McRae, S. S. Modak, G. W. Simmons, D. A. Trochesset, A. R. Kerr, M. H. Thornhill, S. W.

Redding, N. Vigneswaran, S. K. Kang, N. J. Christodoulides, C. Murdoch, S. J. Dietl, R. Markham, and J. T. McDevitt, "Point-of-care oral cytology tool for the screening and assessment of potentially malignant oral lesions," *Cancer Cytopathology*, vol. 128, no. 3, pp. 207-220, 2020. https://doi.org/10.1002/cncy.22236

[31] M. Mermod, E. Jourdan, R. Gupta, M. Bongiovanni, G. Tolstonog, C. Simon, J, Clark, and Y, Monnier, "Development and validation of a multivariable prediction model for the identification of occult lymph node metastasis in oral squamous cell carcinoma," *Head & Neck*, vol. 42, no. 8, pp. 1811-1820, 2020. https://doi.org/10.1002/hed.26105

[32] R. A. Welikala, P. Remagnino, J. H. Lim, C. S. Chan, S. Rajendran, T. G. Kallarakkal, R. B. Zain, R. D. Jayasinghe, J. Rimal, A. R. Kerr, R. Amtha, K. Patil, W. M. Tilakaratne, J. Gibson, S. C. Cheong, and S. A. Barman, "Automated detection and classification of oral lesions using deep learning for early detection of oral cancer," IEEE Access, vol. 8, pp. 132677-132693, 2020. https://doi.org/10.1109/ACCESS.2020.3010180

[33] B. Bhandari, A. Alsadoon, P. W. C. Prasad, S. Abdullah, and S. Haddad, "Deep learning neural network for texture feature extraction in oral cancer: Enhanced loss function*," Multimedia Tools and Applications*, vol. 79, no. 37-38, pp. 27867-27890, 2020. https://doi.org/10.1007/s11042-020-09384-6

[34] P. R. Jeyaraj, B. K. Panigrahi, and E. R. S. Nadar, "Classifier feature fusion using deep learning model for non-invasive detection of Oral cancer from hyperspectral image*," IETE Journal of Research*, vol. 68, no. 6, pp. 4031-4022, 2020. https://doi.org/10.1080/03772063.2020.1786471

[35] R. Prabhakaran, and J. Mohana, "Detection of oral cancer using machine learning classification methods (June 30, 2020)," *International Journal of Electronics Engineering and Technology*, vol. 11, no. 3, pp. 384-393, 2020.

[36] K. Warin, W. Limprasert, S. Suebnukarn, S. Jinaporntham, and P. Jantana, "Automatic classification and detection of oral cancer in photographic images using deep learning algorithms," *Journal of Oral Pathology & Medicine*, vol. 50, no. 9, pp. 911-918, 2021. https://doi.org/10.1111/jop.13227

[37] F. Jubair, O. Al-Karadsheh, D. Malamos, S. A. Mahdi, Y. Saad, and Y. Hassona, "A novel lightweight deep convolutional neural network for early detection of oral cancer," *Oral Diseases*, vol. 28, no. 4, pp. 1123-1130, 2022. https://doi.org/10.1111/odi.13825

[38] G. Tanriver, M. S. Tekkesin, and O. Ergen, "Automated detection and classification of oral lesions using deep learning to detect oral potentially malignant disorders," *Cancers*, vol. 13, no. 11, pp. 2766, 2021. https://doi.org/10.3390/cancers13112766

[39] H. Lin, H. Chen, L. Weng, J. Shao, and J. Lin, "Automatic detection of oral cancer in smartphone-based images using deep learning for early diagnosis," *Journal of Biomedical Optics*, vol. 26, no. 8, 2021, Art. no. 086007. https://doi.org/10.1117/1.jbo.26.8.086007

[40] S. Camalan, H. Mahmood, H. Binol, A. L. D. Araujo, A. R. Santos-Silva, P. A. Vargas, M. A. Lopes, S. A. Khurram, M. N. Gurcan "Convolutional neural network-based clinical predictors of oral dysplasia: Class activation map analysis of deep learning results," *Cancers*, vol. 13, no. 6, pp. 1291, 2021. https://doi.org/10.3390/cancers13061291

[41] B. R, Nanditha, A. G. Kiran, H. S. Chandrashekar, M. S. Dinesh, and S. Murali, "An Ensemble Deep Neural Network Approach for Oral Cancer Screening," *International Journal of Online Engineering*, vol. 17, no. 2, 2021. https://doi.org/10.3991/ijoe.v17i02.19207

[42] A. Paderno, C. Piazza, F. D. Bon, D. Lancini, S. Tanagli, A. Deganello, G. Peretti, E. D. Momi, I. Patrini, M. Ruperti, L. S. mattos, and S. Moccia "Deep learning for automatic segmentation of oral and oropharyngeal cancer using narrow band imaging: Preliminary experience in a clinical perspective," *Frontiers in Oncology*, vol. 11, Art. no. 626602, 2021. https://doi.org/10.3389/fonc.2021.626602

[43] R. Dharani, and S. Revathy, "Detection of oral cancer using deep learning," *Journal of Physics: Conference Series*, vol. 1911, no. 1, 012006, 2021.

[44] B. Song, S. Sunny, S. Li, K. Gurushanth, P. Mendonca, N. Mukhia, S. Patrick, S. Gurudath, S. Raghavan, T. Imchen, S. Leivon, T. Kolur, V. Shetty, V. Bushan, R. Ramesh, N. Lima, V. Pillai, P. Wilder-Smith, A. Sigamani, A. Suresh, M. Kuriakose, P. Birur, and R. Liang, "Mobile-based oral cancer classification for point-of-care screening," *Journal of Biomedical Optics*, vol. 26, no. 6, 2021, Art. no. 065003. https://doi.org/10.1117/1.jbo.26.6.065003

[45] D. Sharma, V. Kudva, V. Patil, A. Kudva, R. S. Bhat, "A Convolutional Neural Network Based Deep Learning Algorithm for Identification of Oral Precancerous and Cancerous Lesion and Differentiation from Normal Mucosa: A Retrospective Study*," Engineered Science*, vol. 18, pp. 278-287, 2022. http://dx.doi.org/10.30919/es8d663

[46] K. Ramezani, and M. Tofangchiha, "Oral cancer screening by artificial intelligence-oriented interpretation of optical coherence tomography images*," Radiology Research and Practice*, 1614838, 2022. https://doi.org/10.1155%2F2022%2F1614838