The use of artificial intelligence in the diagnosis and prognosis of oral cancer

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Abstract

Artificial intelligence has gained the interest of the medical research field, aiming to introduce it in the diagnosis approaches, the management and monitorization of different diseases. In dentistry, its applicability for multiple pathologies, among which the detection and diagnosis of oral cancer, has proven important advantages. This present review aims to describes the applicability of artificial intelligence in oral pathology, focusing on oral cancer, outlining the advantages, limitations and future perspective for this technology. By introducing this technology in the everyday dentistry practice, for dentists and specialists can undoubtedly improve the quality of care.

Keywords: Oral cancer, artificial intelligence, early diagnosis, oral pathology

INTRODUCTION

Diagnosing oral cancer is of high importance in dentistry. It has however sometimes been neglected due to inconsistency in the competency of diagnosis among clinicians. The motivation for investigating this topic is to bring light on new technological advances that can be used to help both newly qualified and experienced clinicians to provide the best care possible for their patients.

Artificial intelligence started in the 1940-1960s [1] but since then it has become the defining technology of the modern era, improving in leaps and bounds since its beginning. Today, we use AI in our daily lives, most often without notion. AI has encapsulated the world and has made significant changes in the medical field. In dentistry AI can be used in all parts of the patient's care, including diagnosis, prognosis and decision making. AI has been used across the board in dentistry; examples including radiology, orthodontics, periodontics, endodontics and oral pathology. It is mainly used in oral pathology for detecting oral lesions. It can also help to differentiate between lesions that appear radiologically similar but clinically different. The time taken to make this diagnosis is considerably lower than without the use of AI. One study found the difference in time to be 23.1 mins for clinicians diagnosis in comparison to 38 seconds for an AI aided diagnosis [2]. Oral cancer is a malignant disease which leads to many fatalities worldwide. It is unfortunately usually detected in the later stages of the disease and therefore increases the treatment time, cost and morbidity rate. Early detection of oral cancer can significantly improve the survival rate by 75%-90% [3]. Already established screening methods can be used alongside AI to provide a proficient diagnosis.

Large amounts of research has been conducted around the application of AI in oral pathology. AI can be utilized in the diagnosis and prognosis of oral cancer extends beyond screening and initial detection. It also finds application in histological evaluation, where it can assist pathologists in analyzing tissue samples. AI algorithms can process vast amounts of histological data, aiding in the classification and grading of oral lesions. This capability not only enhances the accuracy and speed of diagnosis but also supports treatment planning and decision-making processes [4].

AI plays a dynamic role in dentistry, particularly in the diagnosis and prognosis of oral cancer. Its implementation in various stages, including screening, diagnosis, and histological evaluation, offers substantial benefits. By augmenting the expertise of clinicians and enabling the analysis of diverse imaging modalities, AI improves the accuracy and reliability of diagnoses. As technology continues to advance, the integration of AI in dentistry holds great promise for the early detection and management of oral lesions, ultimately improving patient outcomes [4].

This literature review will set out to review the applications of AI in the diagnosis and prognosis of oral cancer. It will establish criteria to include and exclude articles and proceed to compare results. All articles reviewed will be original experiments.

Aim and objectives

The aim of this review is to assess the existing literature on the use of artificial intelligence in the diagnosis and prognosis of oral cancer, within the last 10 years. Specifically, the objective is to evaluate the effectiveness, limitations, and potential challenges associated with AI-based approaches and provide a comprehensive overview of the progress and implications of AI in oral cancer management.

The scope of this literature review encompasses a broad range of studies that use different modalities of oral cancer screening in conjunction with AI. Different AI methods, such as machine learning, deep learning, as well as their integration with imaging modalities, molecular data, and clinical parameters are all reviewed. The validity and reliability, advantages and disadvantages are all to be reviewed.

MATERIAL AND METHODS

This literature review seeks to evaluate current research on the use of Artificial intelligence in diagnosis and prognosis of oral cancer within the last 10 years. Search engines were used to find the articles. The search engines used were Google scholar, PubMed, Science Direct, SCOPUS and Cochrane library.

In the advanced search, the words Artificial intelligence (OR Machine learning OR deep learning) AND diagnosis AND prognosis AND oral cancer OR premalignant lesions were all used in the search criteria these key words 101 articles were yielded. Both in vivo and in vitro studies were used in the review. These articles included a vast array of articles that were not specific to the line of study. Many of these articles were also not accessible as they were not free.

An Inclusion and exclusion criteria was then applied in order to precisely find articles that were related to the line of study. The inclusion criteria was limited to articles that have been published in the last 10 years. These articles all had to be written in the English language and had to be full texts. It was also necessary for the articles to have quantifiable results so that it was possible to compare them later in the discussion part of the review. The articles also had to include the key words and could not deviate from this subject. All articles that were reviewed in this literature review were original research.

The exclusion criteria consisted of studies that were not written in the English language, review articles and articles that did not present original data. The exclusion criteria of free full texts markedly reduced the number of articles that were able to be used in this study.

The search was carried out using advanced search on the search engines and the criteria was also checked manually. Preceding this a total of 15 articles were found that fit all the criteria.

RESULTS

The results of different papers were presented in different manners, for example some studies evaluated the results of a network in terms of specificity or sensitivity while others used precision or accuracy or recall. The studies based on the implications of artificial intelligence rely on the focus on deep learning technology and machine learning.

1.1. **Deep learning**

1.1.1. Photographic imagery

Uthoff et al. [5] developed a unique dual-modality, dual-view point of care oral cancer screening device. This device utilizes white light and autofluorescence imaging used on a smartphone platform, allowing for early detection of pre-cancerous and cancerous lesions in the oral cavity. In a study involving 170 image pairs, the device's performance was evaluated against the gold-standard diagnosis of an on-site specialist. The remote specialist, along with a convolutional neural network (CNN), successfully classified the images as either 'suspicious' or 'not suspicious. Data was taken from 99 patients for the CNN analysis and remote diagnosis. The AUC of the CNN was found to be 0.908. The sensitivity of the convolution neural network was found to be 0.85 and the specificity was found to be 0.8875.

A study conducted by Welikala et al. [6] produced an app named Memosa to record pictures of oral lesions from a smart phone. MeMosa annotate is a separate browser that is made by the company to create a large data set of well annotated lesions which can be then used by AI algorithm to detect early or potentially malignant lesions. 2155 oral cavity images from 1085 individuals were used in this study. 1744 images were used as the training set and 204 were used as the testing set. The pictures consisted of lesions and pictures without lesions. These images were taken from 3 different source: MeMosa app, images annotated by clinicians, images from the web. Memosa annotate was then also used to add more data to the database and these lesions were separately analysed by 3-7 clinicians. They were of different areas of the oral cavity. Welikala investigated the convolutional neural networks' ability to classify images and identify objects. The precision, recall, and F1 score for classifying images with lesions were 84.77%, 89.51%, and 87.07%, respectively. The object identification of lesions achieved a precision of 46.61%, and a sensitivity of 37.16% [6].

Jubair et al. [7] analysed a dataset of 716 clinical images depicting different tongue lesions. The images were categorized into "suspicious" lesions (236 images) and benign lesions (480 images) and were collected over a four-year period from 543 patients using various cameras and smartphones. To ensure data integrity, the dataset was randomly divided into a training set (79%), a validation set (7%), and a test set (14%), with redundancy checks performed to avoid overlap between the image sets. Jubair et al developed a lightweight convolutional neural network which used a pretrained EfficienctNet-B0 as the learning model. Jubair et al found the mean specificity to be 84.5%, with a sensitivity of 86.7% and an AUC for of 0.928 for the EfficienctNet-B0 model.

Sunny et al. [8] investigated the usage of a smart tele-cytology point-of-care platform for oral cancer screening. A total of 11981 images were used in the training, development and validation of the model, the model used was an existing ANN named Inception V3. The model produced a sensitivity of 89%, a specificity of 100% and an overall accuracy of 90% (*Table1*).

1.1.2. Radiologic imaging

Another study conducted by Kirubabai et al. [9] utilizes a deep learning algorithm to classify oral MRI images as either normal or abnormal. The study used a Convolutional neural network classification method and used this to further diagnose cancerous regions in images as either Mild or severe. The study used 160 cancer affected oral images. Kirubabai et al. analyzed the performance of the CNN with and without data augmentation. The study found that using the CNN with data augmentation yielded a selectivity of 98.6%, a sensitivity of 99.1% and an accuracy of 99.7%. The CNN without data augmentation yielded a selectivity of 93.7%, a specificity of 94.1% and an accuracy of 95.6%.

Ariji et al. [10] conducted a study to evaluate the effectiveness of deep leaning classification of images for the diagnosis of lymph node cancer. CT images were used of 127 images that were already proven histologically lymph node metastasis and 314 that did not, and 45 with OSCC. The deep learning methods were then compared with experienced radiologist opinions. Deep learning AUC was 78.2% sensitivity 75.4% and specificity 81.0% but these results did not differ considerably from the results of the radiologists (*Table 1*).

1.1.3. Numerical data

Adeoyo et al. [11] investigated the applications of deep learning to predict the malignant transformation free survival of oral potentially malignant disorders. Data was collected from 716 patients who underwent biopsy for oral leukoplakia, oral lichen planus, or oral lichenoid lesions. 573 patients were used for the training of the algorithm and 143 unseen cases were used as the test set; the patients that were used for the test set were randomly selected in order to remove any possible bias from the results. Adeoye et al investigated 5 different algorithms, cox-ph, cox-time, DeepHit, DeepSurv, and RSF. The C-index and the IBS of the different algorithms were found to be 0.83 and 0.03 for Cox-ph, 0.86 and 0.06 for Cox-time, 0.86 and 0.08 for DeepHit, 0.95 and 0.04 for DeepSurv, and finally 0.85 and 0.03 for RSF.

Adeyo et al found that the DeepSurv algorithm produced the best discriminative performance, while the RSF algorithm produced better calibrated probability estimates.

Kim et al. [12] performed a study on the effectiveness of deep learning techniques to calculate survival predictions of patients who suffered from oral cancer. A total of 255 patients' data was used for the study, with 141 patients being in either stages 1,2 or 3 of cancer, and 114 patients having stage 4 cancer. The data set was split 70/30 into the training set and the testing set. Three different deep learning algorithms were used, DeepSurv, Cox proportional hazard (CPH) and Random survival forest. The Random survival forest yielded a C-index of 0.764, the DeepSurv algorithm yielded a C-index of 0.781, and the CPH produced a C-index of 0.694 for the training sets. The decision tree was much better at predicting survival rates with AUC of 0.840, sensitivity of 0.917, and specificity of 0.576.

Alabi et al. [13] investigated the effects of machine learning applications for the prediction of locoregional recurrences in early oral tongue cancer using a web based prognostic tool. A total of 311 patients' numerical data was used for the study, 165 of those patients being male and 146 being female, with the data set being split into a 70/15/15 ratio of the training set, validation set, and the testing set respectively. An ANN was used as the deep learning algorithm in this study. The ANN yielded an overall accuracy of 92.7%, a selectivity of 71.2%, a specificity of 98.9% and a C-index value of 97.3% (*Table 1*).

1.2. Machine learning

1.2.1. Photographic imagery

The study conducted by Duran-Sierra et al. [14] aimed to develop a method to classify oral lesions as either precancer/cancer or healthy using a special type of imaging called multiparametric autofluorescence lifetime imaging (maFLIM).

To classify the images, the researchers used four different models: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), linear Support Vector Machine (SVM), and Logistic Regression. They determined an optimal score threshold through analysis, and if an image's score was above the threshold, it was classified as precancer/cancer; otherwise, it was considered healthy. They also evaluated the effectiveness of combining different types of features (spectral and time-resolved) for classification.

The SVM model performed best with spectral-only features, while the QDA model performed better with time-resolved-only features. So, they created an ensemble classifier by combining the top three spectral features from the SVM model and the top three time-resolved features from the QDA model. They evaluated the performance of each classifier using ROC-AUC analysis. The ensemble classifier achieved the highest ROC-AUC value of 0.81, indicating good performance. The SVM-QDA classification model yielded the highest cross-validation sensitivity (94%), specificity (74%), and F1-score (0.85).

Rahman et al. [15] used Machine learning algorithms with H&E-stained biopsy slides which were collected from diagnostic centres. Microscopic digital imaging was performed, and the images were graded and labelled. Data pre-processing techniques were applied to eliminate staining differences in the captured images. These images were then tested with five classifiers (SVM, KNN, decision tree, logistic regression, and linear discriminant) using five-fold cross-validation. The decision tree classifier performed the best with an accuracy of 99.78%. The decision tree classifier was selected as the most suitable classifier. AUC was 0.99. The accuracy of classifiers generally increased with the size of the training data. sensitivity was found to be 99.7% and specificity 100%

Alhazmi et al. [16] investigated the effects of artificial intelligence and machine learning and its uses in the prediction of oral cancer. The studied developed an artificial neural network (ANN) that aided in predicting the individual's risk at developing oral cancer. The model consisted of one hidden later in addition to the input and the output later. The attributes that were included composed of 29 variables that were given to everyone in order to develop the final model. 138 cases were selected, with 73 being eligible to the criteria. 22 of the 73 cases were benign or pre-malignant cases, while the remaining 51 cases were malignant. 54 cases were used as the training set and 19 as the testing set. The sex of the patients was split with 36 being male and 37 being female with the mean age of the patients being 55 years. Alhazmi et al found that the average sensitivity of the artificial neural network was 85.71% whereas the specificity of the model was found to be 60%. The accuracy of the network for the prediction of oral cancer was 78.95% (*Table 1*).

1.2.2. ***Optical coherence tomography (OCT)***

James et al. [17] focused on the automated interpretation of Optical Coherence Tomography (OCT) images for oral cancer detection. Two approaches were implemented: Artificial Neural Network-Support Vector Machine (ANN-SVM) model and a simple score algorithm. Patients undertook incision/punch biopsy from the same lesion site where the OTC images were taken. The majority of patients were male, the median age of the patients being 45 years old and 80% had a history of tobacco usage. A total of 3594 images were used, 70% used for the training set and 30% used for the cross validation set. The algorithm was capable of identifying OSCC from others with a sensitivity of 93% and a specificity of 74%. The algorithm produced by james et al was not able to differentiate between the different grades of dysplasia, however it could be differentiated from normal/benign with a specificity of 76% and a sensitivity of 95% (*Table 1*).

1.2.3. ***Numerical data***

Omar et al. [18] developed a prediction model using machine learning in order to predict 5-year overall survival among patients with oral squamous cell carcinoma. This model was used in comparison to a prediction model created by the TNM clinical and pathological stage. The study was conducted over a span of 7 years with a total of 33065 patients taken from the national cancer database. The mean age of the patients was 64.6 years, with 59.9% of the population being male and 90.1% being white.

The model was created using the azure machine learning studio and the data was split 80/20 with the former being used as a training set and the latter as a test set. Several different 2-class models were considered, including decision forest, decision jungle, logistic regression, and neural network. The decision forest classification model was the most robust out of the models investigated with an AUC of 0.8, a precision and accuracy of 71% and recall of 68%. In comparison the same model using only pathological and clinical TNM staging data was less accurate with an AUC of 0.68, an accuracy of 65%, a precision of 69% and a recall of 52%.

Bur et al. [19] conducted a study to predict nodal metastasis in OSSC. Patients who had undergone surgery to primary tumour excision and neck dissection with T1-2N0 between the years 2007- 2013 were identified using national databases and 5 variables were used to predict metastasis. Data was collected on 278 patients and machine learning algorithms were then used to predict nodal metastasis. The decision forest algorithm yielded the highest results with AUC of 0.840 sensitivity of 0.917 and specificity of 0.576 (*Table 1).*

Table 1. Summarization of studies involving the use of AI

Reference	Type of deep/ machine learning	Type of lesion	Sensitivity (%)	Specificity
Uthoff et al. [5]	Deep learning	Pre-malignant/ Malignant	85	88.75
Kirubabai et al. [9]	Deep Learning	Normal/ abnormal	98.6	99.1
Duran-Sierra et al. [14]	Machine Learning	Pre-malignant/ Malignant	94	74
Rahman et al. [15]	Machine Learning	Pre-malignant/ Malignant	99.7	100

James et al. [17]	Machine Learning	Normal, benign, potentially malignant	92	79ut
Welikala et al. [6]	Deep Learning	Normal/ premalignant	89.51	84.77
Omar et al. [18]	Machine Learning	Oral squamous cell carcinoma	68	71
Adeoyo et al. [11]	Deep Learning	oral leukoplakia, oral,lichen planus, or oral lichenoid lesions		
Alhazmi et al. [16]	Machine Learning	Pre-malignant/ Malignant	85.71	60
Jubair et al. [7]	Deep Learning	Suspicious/ benign	86.7	84.5
Kim et al. [12]	Deep learning	Malignant lesions	91.7	57.6
Bur et al. [19]	Machine learning	Metastatic lymph node	91	57.6
Ariji et al. [10]	Deep learning	Metastatic/ normal lymph nodes/ OSCC	78.2	75.4
Sunny et al. [8]	Deep learning	Potentially malignant/ malignant lesions	89	100
Alabi et al. [13]	Machine learning	Previously treated tongue cancer	71.2	98.9

DISCUSSIONS

Oral cancer poses a growing health concern in several low- and middle-income countries, particularly in South and Southeast Asia [5]. To address this issue in high-risk populations residing in remote areas with limited infrastructure, Uthoff et al. [5] developed a unique dual-view point-of-care oral cancer screening device. This device utilizes autofluorescence imaging and white light imaging on a smartphone platform, allowing for early detection of pre-cancerous and cancerous lesions in the oral cavity. This study was able to successfully demonstrate that deep learning methods are able to distinguish between cancer and pre-cancer lesion. Currently the gold standard for cancer detection is done by a clinician to verify the parameters. A limitation of this study could be that the comparison against the deep learning itself is biased and subjective.

Another study conducted by Welikala et al. [6] produced an app named Memosa to record pictures of oral lesions from a smart phone. MeMosa annotate is a separate browser that is made by the company to create a library of well annotated lesions which can be then used by AI algorithm to detect early or potentially malignant lesions. The study investigated CNNs ability to classify images as well as deduce object detections. Image classification describes the ability of a network to classify an image into a certain class according to the images visual content, while the object detection refers to the networks ability to determine where an object is located in the image itself and which class that object belongs to. The results showed that the algorithm was a lot better at classifying images than it was with object identification. This may be because object identification is more obscure as lesion margins or presentation may vary. Once a lesion is established however it is easier to classify into categories of benign and potentially malignant.

From the results that were shown in the previous section in it can be seen that the object classification accuracy is extremely poor, with the precision being nearly half as accurate as the image classification. This shows that while convoluted neural networks can be very effective at image classification, more training is needed in order to improve the results of object classification, this could be done by using larger data sets, training the network for longer or changing/improving the methodology that the network uses to identify the objects position.

The results for image classification obtained in this study are similar to the research conducted by Uthoff et al. [5] whereby the overall accuracy of the two different CNN models harboured similar results when it came to image classification. The number of images used for the training set in the study (1744 photographs) conducted by Welikala et al. was substantially higher than that of the amount used in the study by Uthoff et al (170 photographs). This could suggest that while the amount of data supplied to the network increases the reliability of the study, the amount of data that is used to build the network does not necessarily impact the results as much as the actual framework and build of the network itself. Thus, suggesting a more rigorously developed CNN could provide better and more accurate results with a smaller data set compared to a less proficiently developed CNN with a larger data reserve as its training set.

The study conducted by Kirubabai et al. [9] used a deep learning algorithm to classify oral MRI images as either normal or abnormal. The oral cancer detection system proposed in this study, employing a CNN classification approach, achieves a detection rate of 99.3%. The CNN network has been used to classify images as normal or abnormal in this study. The efficacy of this study shows very high results in all 3 areas of sensitivity, specificity and accuracy. In comparison to the study conducted by Uthoff et al, the sensitivity and specificity results achieved by Kirubabai et al. were over 10% higher than the prior. The study conducted by Welikala also used CNN networks to classify images for referral. This also showed high precision which connotes that CNN networks are good at classifying images. The study by Welikala however yielded much lower results when it came to object detection. This suggests that although CNN networks may have larger scale use for image classification, when it comes to object detection, it could have limitations. The Welikala et al. [6] study however has limitations of its own, it was not able to find a conclusive way to come to a decision of object detection among clinicians. Hence, this is why the object detection using CNN networks may have been less valid as the manual input itself could have had inconsistencies.

Jubair et al. [7] analysed a dataset of 716 clinical images depicting different tongue lesions. The images were categorized into "suspicious" lesions (236 images) and benign lesions (480 images) from images collected over a four-year period from 543 patients using various cameras and smartphones. 3 different models were used each yielding very similar results. This shows that the model itself may not have a direct impact on the results, instead the input and methodology for harboring the results is more important. Understanding these studies can learn to be more stringent with the methods and imputation of data.

Overall photographs coupled with AI were a very good method of classifying oral lesions. Work still needs to be done on object identification, however having a platform that is easily accessible to prevent those that may potentially be at risk of cancer from late diagnosis can really help the prognosis of the disease. These methods should be continually implemented as the benefits are large.

Arji et al. [10] found that there was no significant difference between the deep learning image classification in comparison to radiologist experienced opinion. The high results and similarity with the radiologists show that deep learning can be used effectively. One limitation Is that comparing deep leaning with radiologist opinions means that that the deep learning algorithm can never surpass a clinician’s opinion as clinicians are currently the only means of validation.

Kim et al. [12] found that deep learning methods can be used to predict the survival of patients that have been diagnosed with OSCC. Predicting the survival rates predicts the prognosis of the disease. When compared another numerical study by Alabi et al. which used deep learning with results also being conclusively good, it shows that numerical data in conjunction with AI can have implications in understanding cancer prognosis and also in patient management.

Machine learning has many applications in classifying oral lesions. This aids both the diagnosis and the prognosis aspect of the disease. The study conducted by Duran-Sierra et al. [14] aimed to develop a method to classify oral lesions as either precancer/cancer or healthy using a special type of imaging called multiparametric autofluorescence lifetime imaging (maFLIM). They used this method on real images taken from patients with oral cancer. To classify the images, the researchers used four different models: Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), linear Support Vector Machine (SVM), and Logistic Regression. They trained these models using 34 maFLIM images of oral lesions and healthy tissue. The models created a map that showed the probability of each pixel being precancer/cancer or healthy. They also calculated an overall score for the image based on the average of the probabilities for all the pixels. They determined an optimal score threshold through analysis, and if an image's score was above the threshold, it was classified as precancer/cancer; otherwise, it was considered healthy. They also evaluated the effectiveness of combining different types of features (spectral and time-resolved) for classification [14].

Overall, the study showed that the optimized SVM-QDA ensemble classifier using maFLIM features was effective in detecting oral precancerous and cancerous lesions [14]. This is a very beneficial use of AI as it not only helps with diagnosis of lesions, however the prognosis of cancer is much better when it is detected early, and this study showed promising results. One aspect of AI in all the studies mentioned is that manual input must be first used to train the datasets. This means that this AI model is able to detect pre-cancer/ cancer only based on its training from its own knowledge, instead it relies on pre-existing data. This questions the validity of the results as if the input data is incorrect then the results from the algorithm will also be incorrect. In comparison to deep learning methods whereby the algorithm is able to build up from existing neural networks studies as such using machine learning may be limited. This study has its advantages of being in VIVO as this becomes time saving. Real time images of the oral cavity allow for high degrees of accuracy and results delivered very quickly rather than have to wait for the lab to confirm results.

Another study conducted by Rahman et al. [15] also used Machine learning algorithms. H&E-stained biopsy slides were collected from diagnostic centers. Microscopic digital imaging was performed, and the images were graded and labelled. Data pre-processing techniques were applied to eliminate staining differences in the captured images. Colour channeling and contrast adjustment were performed. Various nucleus segmentation techniques such as Otsu's segmentation, Watershed segmentation, and MSER were applied, and a combination of Otsu's method with morphological operations (erode and dilate) was used for nucleus segmentation.

James et al. [17] focused on the automated interpretation of Optical Coherence Tomography (OCT) images for oral cancer detection. Two approaches were implemented: a simple algorithm-score and an Artificial Neural Network-Support Vector Machine (ANN-SVM) model. Multiple images of oral mucosal lesions were captured and evaluated by a trained oral physician and a non-reference image quality evaluator. Images with low quality and artifacts were removed from the dataset. The remaining images were analysed alongside their histopathological or clinical diagnosis as the gold standard. The performance of each neural network model was evaluated in terms of sensitivity, specificity, and accuracy for distinguishing malignant and dysplastic images.

Overall, the proposed methods achieved high detection rates compared to previous studies, demonstrating the potential of automated interpretation of OCT images for oral cancer detection. Overall, the study demonstrated the clinical application of OCT imaging in triaging patients for oral cancer detection, with the potential to improve diagnostic accuracy and facilitate timely interventions. The OTC imaging was capable of portraying oral cancer with a specificity of between 78-94% and a sensitivity of between 85-92%, thus showing that the use of OCT imaging can be very effective in the diagnosis of OSCC [17].

Omar et al. [18] conducted a study where they developed a machine learning-based prediction model to estimate the 5-year overall survival of patients diagnosed with oral squamous cell carcinoma. They compared this model with a prediction model based on the TNM clinical and pathological stage. Several 2-class models, including decision forest, decision jungle, logistic regression, and neural network, were considered. The development of the model utilized all available variables. The model's performance was assessed by testing it on a separate dataset, and the results were analysed. Among the investigated models, the decision forest classification model demonstrated the highest robustness, with an AUC of 0.8, precision and accuracy of 71%, and a recall of 68%. In contrast, the same model using only pathological and clinical TNM staging data showed lower accuracy, with an AUC of 0.68, accuracy of 65%, specificity of 69%, and sensitivity of 52%. The study conducted by Omar et al. demonstrates that in settings where abundant data is accessible, the utilization of machine learning and artificial intelligence can significantly enhance healthcare outcomes.

Adeyo et al. [11] investigated the applications of deep learning to predict the malignant transformation free survival of oral potentially malignant disorders. The data, which included demographic, clinical, pathological, and treatment information, was obtained from the hospital's electronic health record system. The main objective of the study was to predict the time it takes for these oral lesions to transform into malignancies. The data underwent cleaning and transformation, and five machine learning algorithms were utilized for modelling purposes. The most effective model was then externally validated using an independent dataset. Finally, the final model was deployed using a web-based interface. Descriptive statistics were conducted using SPSS, while the models were implemented using Python. Adeyo et al found that the DeepSurv algorithm produced the best discriminative performance, while the RSF algorithm produced better calibrated probability estimates. The high results of this study show that the time taken for lesions to become malignant can be assessed. The biggest drawback of this study however is that the patients who presented to biopsy all presented at different times during the manifestation of the disease. This study does however show that when a patient presents with a lesion in a certain stage it is possible to estimate the time it would take for malignancy. This again aids the prognosis of the disease.

One of the notable advantages of utilizing AI in oral cancer diagnosis and prognosis is the potential for enhanced accuracy as research progresses and algorithms are further developed and refined. With continued investigation and the advancement of AI training techniques, the predictive capabilities are expected to improve significantly. The strength and quality of the input data, combined with robust methodologies, will contribute to more reliable and robust results.

CONCLUSIONS

Organize conclusions which emerge from the study. In the end state: a) contributions to be acknowledged but which do not justify paternity right; b) thanks for technical support; c) thanks for financial or material support.

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