REVIEW

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Artificial Intelligence Innovations in Understanding Oral Submucous Fibrosis: A Nouvelle Modernistic Approach: A Systematic Review

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Abstract

Background: Oral submucous fibrosis (OSMF) is a common precancerous condition prevalent in the South Asian continent. An immediate diagnosis and identification of this lesion is essential to prevent its malignant transformation. Artificial intelligence can analyze data, patient records, and clinical photographs to finalize a treatment plan in oral submucous fibrosis patients by the oral pathologist and clinicians' intervention. The current study aimed to establish the key role of machine learning software in diagnostic intervention and management of oral submucous fibrosis in the mass population with ease for most health professionals. **Material & Methods:** We searched relevant databases like PubMed, Scopus, Web of Science, Cochrane, and Google Scholar using keywords like artificial intelligence, machine learning, treatment planning, diagnosis, oral submucous fibrosis, image analysis, predictive modeling, and deep neural networks. **Results:** Nine studies were selected after all scrutiny, with suggested outcomes under AI that can be utilized to understand oral submucous fibrosis intervention. Machine learning is a helpful tool in fabricating image prediction models under neural networks. This can be an important diagnostic aid for oral health professionals. **Conclusions:** In the field of oral pathologies, AI has the potential to enhance diagnostic accuracy and patient care, improve diagnostic outcomes, and improve the prognosis of the disease. However, the development and application of AI in oral healthcare, especially for oral submucous fibrosis patients, is a new frontier for modernistic approaches for future treatment amenities.

Keywords: Artificial intelligence- Machine learning- Diagnosis- Image analysis- Predictive modelling

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Introduction

Oral submucous fibrosis is a precancerous condition affecting the epithelial tissues, and subepithelial mucosal lining causing fibroelastic changes in the juxta epithelial layer leading to irreversible changes in the mucosa tissues causing loss of resiliency of tissues [1]. In the field of oral and maxillofacial pathology, along with old standard techniques for diagnosis and therapeutic intervention to treatment & prognosis of the disease, novel technology has developed over the years, like computerized tomography, magnetic resonance imaging, ultrasound, and Positron emission tomography, in the accurate diagnosis and treatment of diseases [2, 3]. With the advancement of recent diagnostic techniques, various oral diseases have become easy to diagnose clinically and radiographically based on the clinical signs and symptoms and radiographic image analysis using software [4, 5]. Incorporation of Machine learning software in the diagnostic approach of oral submucous fibrosis at an early stage results in better treatment and accuracy at the level of disease prognosis. The use of various artificial intelligence-governed neural networks leads to easy early detection of the pathology with precision and accuracy [6].

Various systems are currently accessible to an anatomical pathologist for nuclear morphometry image analysis. However, a significant limitation of these systems necessitates expensive software and hardware attachments for image acquisition, analysis, and storage. Consequently, a cost-effective alternative for image analysis would be useful for pathologists and researchers alike. ImageJ is an open-source, Java-based image processing and analysis program software that aids researchers in visualizing, inspecting, quantifying, and validating scientific image data. Image analysis allows users to extract information from images in a reproducible manner. ImageJ, being publicly available, presents a practical option for nuclear morphometric assessments on stained sections, offering

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the flexibility to download specific plug-ins directly from the ImageJ website, which is a definite advantage for better and easier diagnosis [7]. In this article, we provide an overview of the current state of research on the use of AI in early diagnosis of oral submucous fibrosis. Oral and maxillofacial pathology, including the types of algorithms and models that have been developed, the challenges and limitations of the technology, and the potential future directions for research and clinical application [2]. We also discuss the ethical and regulatory issues that must be considered when using AI in pathology, such as data privacy, bias, and transparency. By highlighting the potential benefits and limitations of AI in oral and maxillofacial pathology, we hope to stimulate further research and discussion on this important topic.

Materials and Methods

This systematic review was implemented and addressed as per the 2020 PRISMA guidelines for research review guidelines by the diagnostic accuracy testing strategy marked under (PRISMA DATA). The overall data search for this review was performed systematically by searching articles in esteemed databases, including Scopus, Web of Science, Cochrane, PubMed, Embase, and Dimensions, published between January 2018 and September 2024. This research is submitted and registered under the PROSPERO registry (ID: CRD420251041863). The search material only emphasized those articles that included the diagnosis of oral submucous fibrosis at an early stage, performed using different network algorithms under AI machine learning. An amalgamation of various primarily characterized keywords such as computerized learning, modernized machine learning, and neural networks algorithms was preferred for searching [8, 9]. The final results were based on the elements of PICO (problem/patient/person, incursion/ indicator, comparison, and outcome) (Table 1).

Study design

Abstracts and full-text articles were scrutinized in the initial search and were saved for further research. The data search was performed by the title search and search using the research question to proceed with the PRISMA flow chart. At the preliminary level, the search comprised search engines, including PubMed, Scopus, Web of Science, Embase, Dimensions, and Cochrane. In the initial selection, the articles remained 103 in counting. From those 103 articles, double articles and those found unacceptable by the automation tool were dismissed. Hence, after the exclusion of seventy-three articles, 52 were retrieved. Two separate investigators reviewed these fifty-two articles. These articles were scrutinized based on no full text, biased study results, and combined studies other than the short-listed articles. The investigators finally selected eight studies after excluding all the biases and complexities. So, in conclusion, only eight studies were found correct and completely eligible for systematic review. The study follows inevitable inclusion and exclusion criteria as mentioned below.

Eligibility criteria for the study-
Inclusion criteria

1. Eight randomized clinical trial studies were selected after searching various databases.
2. The article must be focused on oral submucous fibrosis associated with artificial intelligence.
3. There should be a non-biased methodology for the AI technology used in the study.
4. An appropriate description of a predictive outcome that can be quantitatively processed.

Exclusion criteria

1. Articles mentioned any other topics of interest in oral submucous fibrosis.
2. Open abstract articles without full text.
3. Articles presented in any other foreign language.
4. Articles with incomplete structure and risk of bias in the study model.

Statistics

Data extraction and management of these eight articles were shortlisted, and the details of the journal's name, author details, and year of publication were critically investigated. The Quality Assessment and Diagnostic Accuracy Tool (QUADAS 2) was used for the assessment using RevMan 5.4 version software for further quality assessment and diagnostic accuracy tool for data extraction. It consists of four main domains: patient assortment, evidence indicator test, reference standards, and patient flow, all through the study and timings of the evidence indicator assessments and reference standard (flow and timing). Each domain is measured to level out the risk of bias criteria in the selected data. Gesticulating questions help the reviewer to judge the risk of bias scope in the study and identify the red zone areas of the selective study model. These selected eight articles were read in total length and engorged in a series of years of publication in a tabular form as a PRISMA flowchart (Figure 1).

Table 1. Description of the PICO (P, Population; I, Intervention; C, Comparison; O, Outcome) Elements

Research Question: What is the application of AI in Early detection of oral lesions, and how? Accurate is it, compared with manual techniques?	
Population	Patient's diagnostic digital photographs and images related to oral and maxillofacial regions [clinical photos, confocal laser endomicroscopy (CLE) Images, intraoral fluorescence images, near-infrared-light transillumination (NILT) images]
Intervention	AI-based models are used for personal identification, age estimation, and gender determination.
Comparison	Expert opinions, reference standards
Outcomes	Measurable or predictive outcomes such as accuracy, sensitivity, specificity,

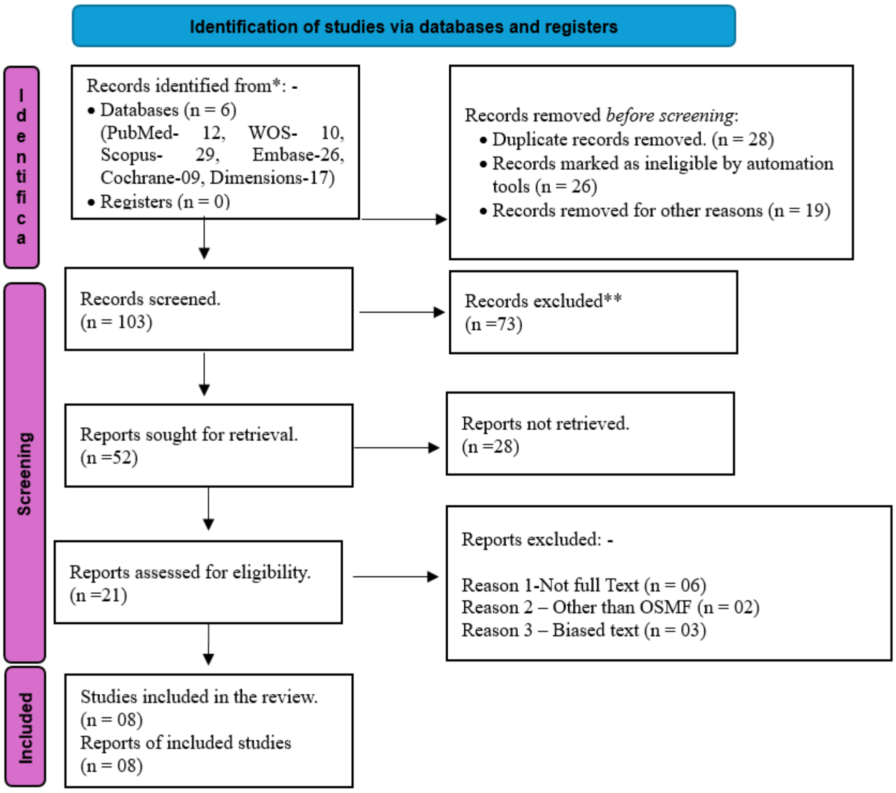

Figure 1. PRISMA 2020 Flow Diagram for New Systematic Reviews which Included Searches of Databases and Registers Only

Results

Eight research articles were evaluated, showing an upgraded quantitative data collection. The collected literature was compiled for the research analysis and shows studies published in the last 10 to 15 years. The studies included in this review emphasize the application of AI in the detection of oral diseases for analysis and clarifying which network shows the most promising results out of different AI algorithms. These AI-based studies have used artificial neural networks like ML software [10], A model with the help of an IoHT device [11], Roboflow machine learning software [12], Diagnosis Oral Diseases Software DODS [13], ImageJ analyzer (version 1.53) software was used for machine learning, ORCHID (Oral Cancer Histology Image Database [15]) and convolutional neural networks (CNNs) (Figure 2). Each network works on competitive grounds for the accuracy of diagnostic results to the best of its ability. Separate sections were compared internally to understand and study the extracted data and determine the most accurate algorithm to use and recommend. The risk of bias estimation was performed using the QUADAS 2 tool for diagnostic tests. In the risk of bias arm of the tool, 75% of the studies reported negligible risk for the patient section 17. Two studies each reported an elevated risk for patient selection. Out of the eight studies, the reference standard was unclear for 75%, and only 25% were at insignificant risk. Because the data feeding in AI technology is highly standardized, and there is no effect of a low time limit in the final output, both aspects were regarded as low-risk categories in all the studies18. All included studies did not mention gender and age specification for oral submucous fibrosis detection and kept it under unclear bias. Following the risk of bias arm of the QUADAS 2 assessment tool, the applicability concern arm showed related results in data extraction (Table 2,3).

In this systematic review, we assessed the studies using AI-based models in the detection of oral submucous fibrosis analysis. The chief advantage of AI-based modes is that they are structured to identify an individual through oral data records, orthopantomographic records, and digital images for pattern analysis. These AI-based models are structured so well and accurately that they overcome the limitations caused by manual human error in analysis. These AI algorithms were compared between studies and the network with the most accurate data analysis and accuracy was selected. All showed positive results in context with the use of machine learning and the use of algorithms for the detection of oral submucous fibrosis at an early stage. The observation under software learning was based on accurate measures, growth with age ratio, kappa coefficient, and F score. The final results were based on the technical modifications and limitations suggested by the software to categorize the data accordingly.

Discussion

The absolute necessity in diagnostic intervention is easy clinical diagnosis at an initial stage. It is crucial to introduce AI in the field of oral medicine for more reliable and consistent diagnosis. Only 15%-20% of the one million oral pre-cancerous lesion biopsies were found to be cancerous. This emphasizes the necessity of

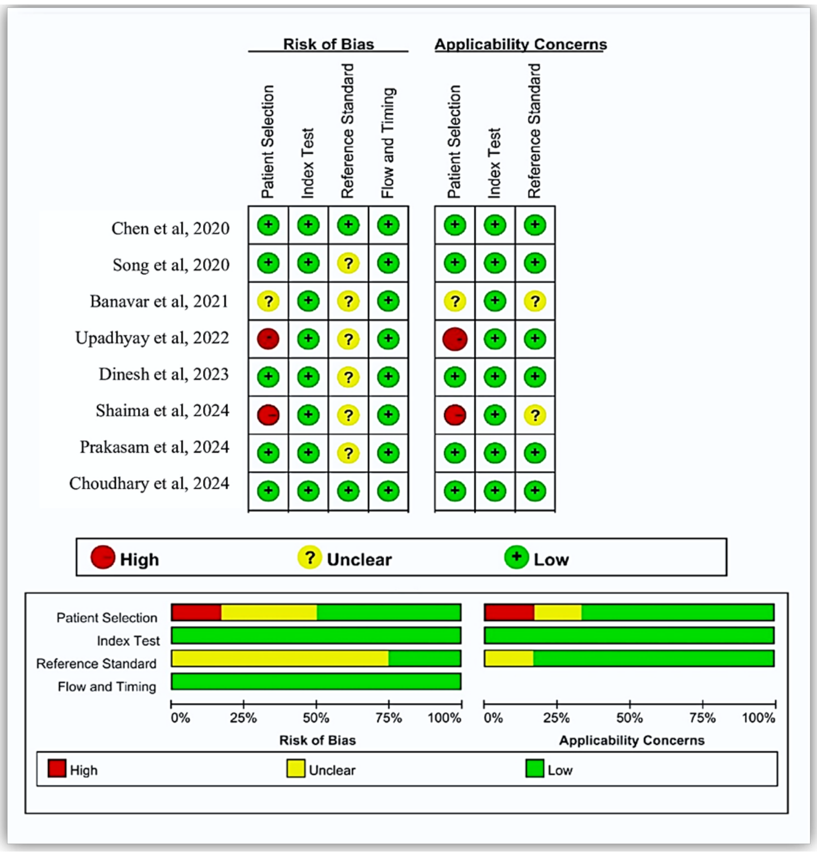

Figure 2. Risk of Bias Assessment and Applicability Concerns Table

computer-aided diagnosis, which enables pathologists to concentrate more on challenging cases rather than sorting through benign tissue. AI systems are used in Oral and Maxillofacial disorders, particularly those dealing with diagnostic imagery and patient-specific predictive analysis. AI systems software is trained on collected datasets, and any biases in these datasets can interpreted by the AI. Randomized control trials like Shaima et al. [14] and comparative studies like Choudhary et al. [15] provide valuable evidence, but more such studies are needed. Oral submucous fibrosis particularly deals with changes in the epithelial layer causing dysplastic changes. With the help of accurate system AI software, at an early stage, it becomes quite easy for the diagnostic clinician

Table 2. General Characteristics of Included Studies

S. No	Author	Country of Origin	No. of images/ photographs for testing	Objective of the study
1	Chen et al. [13]	India	52	This study's objective is to utilize AI for disease diagnosis at an early stage and a better prognosis.
2	Song et al.[17]	China	374	With the aid of machine learning (ML), OSCC and premalignant lesions can be distinguished from normal physical conditions in real-time with accuracy.
3	Banavar G et al. [18]	USA	433	The objective is the potential clinical utility of an AI/ML model for diagnosing Oral diseases at an early stage, opening a new era of noninvasive diagnostics, enabling early intervention, and improving patient outcomes.
3	Upadhyay et al. [12]	India	Not clear	Our objective is to develop a model with the help of an IoHT device for the detection of oral submucous fibrosis in the early stage.
4	Dinesh et al. [11]	India	360	The study objective is early detection of Oral potentially malignant conditions is crucial for early management to attain a better prognosis and overall survival.
5	Shaima et al. [14]	Cairo	3000	The objective of this study was to develop software with all needed feeding data to function as an AI-based program to diagnose oral diseases.
6	Prakasam et al. [10]	India	25	Measure and compare the changes in epithelial thickness and cell morphology in OSMF in comparison with normal mucosa using computer-aided image analysis software.
7	Choudhary et al. [15]	India	150	The objective is to use a specialized database to do advanced research in AI-based histology image analytics of oral cancer and precancer.

Table 3. Outcome of Included Studies

S.No.	Author	Results/Outcomes	Data Assessment
1	Chen et al. [13]	Results show reasonable accuracy in neural network machine learning software.	Accuracy up to 81.3%
2	Song et al. [17]	The ML software used the lasso model for disease detection using salivary biomarker	95% accuracy rate
3	Banavar G et al. [18]	Software evaluated the machine-learning (ML) classifiers using meta-transcriptomic data from saliva samples.	92.3% accuracy rate
4	Upadhyay et al. [12]	A model with the help of an IoHT device for detecting oral submucous fibrosis in the early stage.	Comparative accuracy of 81.56% and 82.7 %
5	Dinesh et al. [11]	Roboflow machine learning software used for early detection of suspected lesions using clinical intraoral images	Model accuracy to be 75% to 88.9%
6	Shaima et al. [14]	(Diagnosis Oral Diseases Software DODS), they utilized clinical images, radiographs, and histopathological photographs,	Accuracy of 87% to 95%
7	Prakasam et al. [10]	The parameters used were cell area and perimeter and epithelial thickness. ImageJ analyzer (version 1.53) software was used for machine learning	Accuracy ranges from 81.5% to 91.0%
8	Choudhary et al. [15]	ORCHID (Oral Cancer Histology Image Database), a specialized database generated to advance research in AI-based histology image analytics of oral submucous fibrosis	The accuracy rate varies between 97.5% to 98.5%

to first verify the clinical condition using AI-guided imaging software. This process becomes convenient for the patient as well as the clinician. The cumbersome process of biopsy/FNAC is kept at 2nd stage of diagnosis. This further highlights the necessity for computer-aided image classification systems that combine quantitative histological feature analysis with fast, comfortable, easy, reliable, and impeccable cancer diagnosis.

A brand-new technique for marking layers in histological sections of multi-layered tissues was introduced by Prakasam et al. [10] by using an AI image-guided software named ImageJ analyzer (version 1.53). This helps in the detection of epithelial dysplastic changes with the help of images taken clinically. In a different study, Dinesh et al. [11], researchers used clinical images of healthy, premalignant, and malignant tissues in 2D sections. By classifying the histopathological tissue sections into normal, oral submucous fibrosis (OSF) without dysplasia, and OSF with dysplasia, a study attempted to increase the stage diagnostic accuracy. The study objective is early detection of Oral potentially malignant conditions is crucial for early management to attain a better prognosis and overall survival. Roboflow machine learning software is used for the early detection of suspected lesions using clinical intraoral images.

The AI software was proven to be 88.9% accurate when compared to the histopathological reporting. Other studies with AI-based approaches have higher prediction accuracy even larger selection sample sizes are necessary. Choudhary et al. [15] include ORCHID (Oral Cancer Histology Image Database) a specialized database-generated software to advance research in AI-based histology image analytics of oral submucous fibrosis. The accuracy rate varies between 97.5% to 98.5%. From a diagnostic perspective, AI has been used to analyze OMF imagery, helping to identify pathologies such as oral cancer, cysts, tumors, and other abnormalities more accurately and efficiently [14, 15 , 16]. ML algorithms used by Song et al. [17] for instance, have been trained to classify and interpret dental radiographs, reducing interpretation errors and expediting the diagnostic process. DL, a subset of ML, has also been utilized in predictive modeling, aiding in prognostic determination for conditions like oral submucous fibrosis and oral squamous cell carcinoma. The inability to understand how different software algorithms are been compared and used in clinical intervention. This issue is further complicated by ethical and regulatory concerns regarding patient data privacy, informed consent, and accountability in the event of AI-induced errors. AI-related studies need to be performed on a larger scale. Addressing these challenges requires a multifaceted approach. All the studies selected in this systematic review are subjectable to better accuracy and reliability. Artificial intelligence-guided software is a new technique for many future perspectives. For data-related issues, collaboration among healthcare institutions to share and aggregate data in a secure, privacy-compliant manner can be beneficial. Also, we could not find a lot of clinical trials that directly examined the effects of AI in the field of OMF pathology, due to issues with ethics and other safety hazards since this still is a nascent technology that we do not know fully about. Hence, we recommend more studies in this regard to ascertain the role of AI as a viable therapeutic modality.

Limitations of the study

We need more original research on the mass population and more neural networks to be included for more accurate and authentic outcomes.

Future perspective

Our study found that the ORCHID (Oral Cancer Histology Image Database) algorithms are responsible for the maximum accuracy percentage, and further studies should be conducted to determine their shortcomings and future scope.

In conclusion, artificial intelligence is the upcoming advanced technology that will provide specific and accurate data for diagnostic purposes. Its use in various fields of medical and dental science has made it a subject of research to understand its applications, limitations, extraordinary approaches, and lacunae before advancing further. The goal of providing upgraded services for the betterment and welfare of patients makes it an essential tool for diagnostic and therapeutic approaches. Different algorithms are meant to have other functional challenges in screening, assessing, and acknowledging the data for Oral submucous fibrosis detection. This study shows a novel approach to oral submucous fibrosis detection at an initial stage. The strength of this study is its unique emphasis on using machine learning to improve data assessment and its simultaneous guidance on using the most effective neural networks for this process.

Author Contribution Statement

All authors contributed equally in this study.

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None.

Conflicts of interest

There are no conflicts of interest.

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