FROM PIXELS TO DIAGNOSIS: CHANGING LANDSCAPE OF ORAL CANCER DETECTION
A SCOPING REVIEW

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INTRODUCTION:

Oral cancer is a significant global health concern & early detection plays a crucial role in improving patient outcomes. Integration of artificial intelligence (AI) with whole slide imaging (WSI) has emerged as a promising approach for oral cancer detection. WSI allows digitization of entire histological slides at high resolution, creating a comprehensive digital representation of tissue samples. Through deep learning techniques, AI models can learn to identify subtle morphological features and patterns indicative of oral cancer with high precision. Pathologists can remotely access digitized slides and leverage AI algorithms to aid in their diagnoses, allowing for expert opinions to be readily available, regardless of geographical barriers.

AIM:

To evaluate the use of artificial intelligence with whole slide imaging in the detection of oral cancer

INCLUSION:

- Studies using AI for automated detection, grading & classification of oral cancer
- Full text articles
- Studies in English language

EXCLUSION:

- Studies using AI/ML for detection & diagnosis of cancers other than oral cavity
- Studies with only abstract published
- Studies not using WSI of human tissue slide
- Studies not using histological image parameters: radiographic, photographic, cytology, genomic data etc)

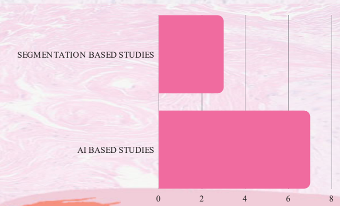
MATERIAL & METHOD:

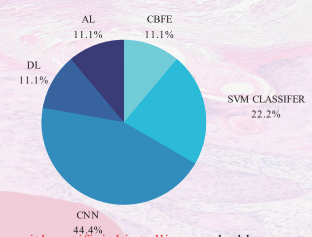
A literature search was performed in PubMed & Google Scholar till 31st May 2023 without period restriction. The key words used were "artificial intelligence", "machine learning", "oral cancer", "diagnosis", "detection", "whole slide imaging." A total of 10 articles fulfilled the inclusion and exclusion criteria and were included. The pertinent data was extracted & recorded.

AUTHOR/YEAR/ JOURNAL/COUNTRY	CANCER SITES & END POINTS	DATA SETS	METHODS	CONCLUSION
Sun YN et al/ 2010/ Microsc Res Tech	Oral Cavity Oral cancer parameters vessels, nuclei, light & dark backgrounds	216 WSI (52, 55, 53, and 56 images of stages I, II, III, and IV of OSCC of 6 patients); Tumor stained by Anti-CD34.	Color Based Feature Extraction system followed by principal component analysis which divided the color features into 4 tissue types.	Specific histo features (vessel area/number/density & nuclei area/number were computed for quantitative differentiation of OSCC stages. Sensitivities of 49.11%, 64.17%,58.55% & 79.60% for OSCC stages I-IV.
Rahman TY et al/ 2018/ JMicrosc	Oral Cavity Benign lesions; SCC	42 WSIs; 476 patches (237 benign lesions; 239 SCC)	Support Vector Machine classifier for automated binary classification of SCC based on texture features namely mean, variance, skewness, kurtosis, energy and entropy (first-order texture feature) from the histogram.	100% accuracy; AUC: 0.92 & 1 89.7% accuracy for data set generated by applying t-test and 100% accuracy for the PCA generated data sets.
Das DK et al/2018/ Tissue Cell	Oral Cavity Healthy tissue; SCC 25 low grades, 15 high grades, & 2 healthy. 3 images from each slide.	126 WSIs (80 images labelled for training patches, 20 for testing (10 for epithelial & 10 for keratin region); One million patches (0.25 million patch from each region).	2 stage approach where 12 layered (7x7x3 channel patches) deep Convolutional Neural Networks are used for segmentation of constituent layers followed by detection of keratin pearl using texture-based feature (Gabor filter) trained random forests.	96.88% detection accuracy of keratin pearls (small datasets with small patches/sub-images within WSI) Could be utilized for oral precancerous screening and OSCC grading.
Rahman TY et al/ 2019/ Tissue cell	Oral Cavity Benign lesions; SCC	42 WSIs. 720 nuclei images segmented automatically	Support Vector Machine classifier for automated binary classification of oral cavity SCC based on shape, texture and color features.	Different classifiers were applied for classification purposes. 99.4% accuracy using Decision Tree Classifier and 100% accuracy using SVM, logistic regression & linear discriminant classifier.
Martino et al[5]/ 2020/ Applied sciences/ Italy	Oral Cavity, SCC	756 training set 100 test set from ORCA	1. Seg Net 2. U-Net 3. U-Net with VGG16 encoder. 4. U-Net with ResNet50 encoder	A novel dataset, ORCA which will allow to conduct new studies on OSCC. This could facilitate the development of molecular characterization deep learning algorithms.
Halicek et al[6]/2020/ Scientific reports	Head & Neck Benign lesions; SCC	228 WSIs (head & neck) 124 WSIs (oral cavity)	Two-dimensional CNN classifier based on the Inception V4 architecture for predicting the probability of cancer on analyzing segmented cavity) patches from WSIs.	85%; AUC: 0.916 -; AUC: 0.944
Das et al[7] /2020/ Neural network	Oral Cavity Benign lesions; SCC with diff tumor patches (well, moderately & poorly differentiated)	156 WSIs, 8321 patches	CNN based multiclass grading classifier for automated classification of differentiation levels in oral cavity SCC.	97.5%
Zhang X et al/ 2022/Cancer Med	Oral Cavity Oral mucosa & Oral cancer	Cohort (n = 62) into high& low-risk groups. OMRS model developed on H&E-sections of 38 oral mucosal biopsies. 14425 patches (6846 OSCC; 7579 oral mucosa)	CNN-based oral mucosa risk stratification model (OMRS) was trained to classify a set of nondysplastic oral mucosa & a set of OC H&E slides	The OMRS model identified OL with a high risk of OC devt. & can potentially benefit OC early diagnosis and prevention. Overall prediction accuracy in testing set of 95.4%; accuracy 94.7% for tumor epithelium & 98.0% for nondysplastic epithelium patches
Lee LY et al/2022/ Front Oncol	Oral Cavity; Identification of nerve structures & diagnosis of perineural invasion in oral cavity SCC	65 WSIs. 540 patches (331 annotation for Perineural invasion, 814 for normal nerve), 10 WSIs for pathological validation	Domain knowledge enhanced yield (Domain- KEY) algorithm as a form of hybrid intelligence to identify nerve structures and diagnose perineural invasion in oral cavity SCC.	Accuracy 89%; Accuracy based on pathological validation based on slide examination 97.5%
Folmsbee et al[10]/2022/ Journal of Pathology informatics/	Oral Cavity Low stage OSCC patients	151 WSIs; 107 clinically low stage OSCC 23 ground truth maps	Active Learning (AL)-modified U-net classifier on the region of interest (ROI) scale	AL shows benefits for generating segmentation results vs randomly selecting images to annotate. AL, with an avg Dice coefficient of 0.461, outperforms RL, with an avg Dice Coefficient of 0.375, by 0.086.

CONCLUSION:

The integration of AI with WSI offers a promising avenue for improving oral cancer detection. By leveraging the power of AI algorithms, early and accurate diagnosis can be achieved, leading to timely interventions and improved patient outcomes. With ongoing advancements in AI technology and the ever increasing availability of digitized slides, the future of oral cancer diagnosis looks promising, bringing us closer to a world where precision medicine is witin reach.





LIMITATIONS:

- WSI relies on high-quality digital scans of tissue slides, which can be time-consuming and resource-intensive to obtain.
- Large size of WSI datasets can pose challenges for AI algorithms in terms of processing and storage requirements.
- WSI may encounter difficulties in accurately capturing subtle morphological features and cellular details, which are crucial for precise diagnosis.
- AI algorithms heavily depend on training data, and the availability of annotated and diverse WSI datasets for oral cancer are limited.
- The interpretation and integration of AI-generated results into clinical practice require careful validation and standardization to ensure their reliability and effectiveness in real-world scenarios.

FUTURE PERSPECTIVE:

In the future, the integration of whole slide imaging with artificial intelligence holds great promise in oral cancer detection. Advanced algorithms and machine learning techniques can analyze vast amounts of digital histopathological images with exceptional precision and speed. This synergy between whole slide imaging and AI has the potential to revolutionize oral cancer diagnosis, enabling early detection and improving patient outcomes

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