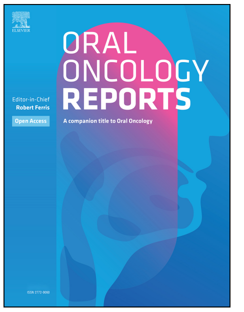

Harnessing Artificial Intelligence for Predictive Modelling in Oral Oncology: Opportunities, Challenges, and Clinical Perspectives

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Title: Harnessing Artificial Intelligence for Predictive Modelling in Oral Oncology: Opportunities, Challenges, and Clinical Perspectives

Abstract: Artificial intelligence (AI) has emerged as a promising tool in oral oncology, particularly in the field of prediction. This review provides a comprehensive outlook on the role of AI in predicting oral cancer, covering key aspects such as data collection and preprocessing, machine learning techniques, performance evaluation and validation, challenges, future prospects, and implications for clinical practice. Various AI algorithms, including supervised learning, unsupervised learning, and deep learning approaches, have been discussed in the context of oral cancer prediction. Additionally, challenges such as interpretability, data accessibility, regulatory compliance, and legal implications are addressed along with future research directions and the potential impact of AI on oral oncology care.

Keywords: Artificial intelligence, Oral oncology, Prediction, Machine learning, Deep learning, Data preprocessing, Performance evaluation, Clinical practice.

Introduction

Oral cancer is a significant contributor to global mortality, ranking as the 17th most prevalent cancer worldwide and 11th most common cancer in Asia. In 2020, the World Health Organization reported over 370,000 new cases of oral cancer, resulting in more than 170,000 fatalities.[1]

Epidemiology and Risk Factors:

The incidence of oral cancer varies geographically, with higher rates observed in regions where tobacco and alcohol consumption is prevalent, such as Southeast Asia and parts of Europe. Additionally, infection with human papillomavirus (HPV) has been identified as a risk factor for certain types of oral cancers, particularly oropharyngeal cancer. Other risk factors include prolonged sun exposure (for lip cancer), poor oral hygiene, dietary factors, and genetic predispositions. Men are at a higher risk of developing oral cancer than women, and this risk increases with age.[2]

Current Diagnostic and Predictive Methods:

The early detection of oral cancer is crucial for improving treatment outcomes and survival rates. The current diagnostic methods include visual examination, palpation, and tissue biopsy. However, these approaches may have limitations, such as subjectivity in interpretation and reliance on the experience of healthcare professionals.[3] In recent years, advancements in imaging technologies, such as optical coherence tomography (OCT) and fluorescence spectroscopy, have enhanced early detection capabilities.[4] Moreover, predictive models based on clinical and pathological features have been developed to estimate the risk of oral cancer development in high-risk individuals.[5] Despite these advancements, challenges remain in accurately predicting individualized risk and optimizing screening strategies for early detection.

Fundamentals of Artificial Intelligence (AI)

Brief History of AI in Healthcare:

Artificial Intelligence (AI) has a rich history in healthcare, dating back to the 1950s, when researchers began exploring its potential applications in medical diagnosis and treatment.[6] Early AI systems focused on rule-based expert systems designed to emulate human decision-making processes. Over the decades, advances in computing power, data availability, and algorithmic techniques have propelled AI into various healthcare domains, including oncology. In the context of oncology, AI has been employed in tasks such as image analysis, clinical decision support, and predictive modelling to improve patient care and outcomes.[7]

Types of AI Algorithms (Table 1):

AI encompasses a diverse set of algorithms and methodologies suited to different tasks and data types. In healthcare and oncology, common AI algorithms include:

Machine Learning (ML):[8-9] ML algorithms learn patterns and relationships from data without explicit programming. Key paradigms within ML include:

- **Supervised Learning:** Algorithms learn from labeled data. Examples include Support Vector Machines (SVM), Random Forests, and Logistic Regression.
- **Unsupervised Learning:** Algorithms find hidden patterns in unlabeled data. Examples include K-means Clustering and Principal Component Analysis (PCA).
- **Reinforcement Learning:** Algorithms learn by interacting with the environment to maximize cumulative reward.

Deep Learning (DL):[10] DL is a subset of ML that employs neural networks with multiple layers to learn complex data representations. Notable DL algorithms include:

- **Convolutional Neural Networks (CNNs):** Used for image classification and segmentation.
- **Recurrent Neural Networks (RNNs):** Used for sequential data analysis, including Long Short-Term Memory (LSTM) networks.

Natural Language Processing (NLP):[11] NLP techniques process and analyse human language data. Examples include:

- **Named Entity Recognition (NER):** Identifies entities in text.
- **Sentiment Analysis:** Determines the sentiment expressed in text.
- **Text Classification:** Classifies documents into predefined categories.

Applications of AI in Oncology:

AI has found numerous applications in oncology, revolutionizing various aspects of cancer care and research. Some key applications include the following.

- Medical Imaging: AI algorithms analyze medical images, such as X-rays, MRI scans, and histopathology slides, to assist in cancer diagnosis, staging, and treatment planning. Deep learning techniques, particularly CNNs, have shown remarkable performance in detecting tumors, characterizing tissue abnormalities, and predicting treatment responses from imaging data.[12]
- Clinical Decision Support: AI-based clinical decision support systems integrate patient data, scientific evidence, and clinical guidelines to assist healthcare providers in making informed decisions regarding cancer diagnosis, treatment selection, and patient management. These systems leverage ML and NLP techniques to analyze heterogeneous data sources, extract relevant information, and generate personalized recommendations tailored to individual patients.[13]
- Predictive Modeling and Prognostication: AI models predict cancer outcomes, such as survival, recurrence, and treatment response, based on patient-specific characteristics, molecular profiles, and environmental factors. These predictive models can aid clinicians in risk stratification, treatment planning, and patient counseling, leading to more personalized and effective cancer care.[14]

Role of AI in Oral Cancer Prediction

Early Detection and Diagnosis:

The early detection of oral cancer is crucial for improving patient outcomes and survival rates. AI plays a significant role in enhancing early detection and diagnosis by analyzing various data modalities, including imaging, clinical, and molecular data. Machine learning algorithms, particularly deep learning models, have demonstrated remarkable performance in analyzing medical images such as X-rays, computed tomography (CT) scans, and magnetic resonance imaging (MRI) to detect suspicious lesions and characterize their features.[15] For instance, convolutional neural networks (CNNs) can automatically segment oral lesions, distinguish benign from malignant lesions, and assess tumor size and invasion depth with high accuracy. Moreover, AI-powered clinical decision support systems leverage patient demographics, risk factors, and symptomatology to assist clinicians in prioritizing high-risk individuals for further evaluation and biopsy, thereby facilitating timely diagnosis and intervention.[16]

Predictive Modeling of Oral Cancer Risk:

In addition to early detection, AI enables predictive modeling of oral cancer risk to identify individuals at an increased risk of developing the disease. These predictive models leverage diverse data sources, including demographic information, lifestyle factors, genetic predisposition, and biomarker profiles, to estimate an individual's likelihood of developing oral cancer over a specific time frame.[17] Machine learning techniques, such as logistic regression, decision trees, and ensemble methods, are employed to develop predictive models that can stratify individuals into different risk categories based on their personalized risk scores. By identifying individuals at high risk for targeted surveillance and preventive interventions, these AI-powered risk prediction models have the potential to reduce the burden of oral cancer morbidity and mortality.[18]

Integration with Imaging and Pathological Data:

Furthermore, AI facilitates the integration of imaging and pathological data to improve the accuracy and reliability of oral cancer predictions. By combining information from various imaging modalities, such as radiographic imaging, endoscopy, and histopathological analysis, AI algorithms can provide comprehensive assessments of lesion morphology, tissue characteristics, and molecular markers associated with oral cancer progression.[19] Deep learning approaches, including multi-modal fusion networks and transfer learning techniques, enable the fusion of heterogeneous data sources to generate integrated predictive models that leverage complementary information from imaging and pathology data. Moreover, AI-powered image analysis tools can assist pathologists in interpreting histopathological slides, identifying subtle morphological features indicative of malignancy, and quantifying biomarker expression levels with high precision and reproducibility.[20] By integrating imaging and pathological data into predictive models to enhance the accuracy of oral cancer risk assessment and facilitate personalized treatment planning tailored to individual patient characteristics.

Data Collection and Preprocessing

Sources of Data in Oral Oncology:

Data collection is a critical step in the development of AI models for oral oncology prediction. Various data sources contribute to this process, including

- Clinical Records: Electronic health records (EHRs) contain comprehensive information on patients' medical history, including demographics, clinical symptoms, diagnostic tests, treatment regimens, and outcomes. These records provide valuable insights into patient disease trajectories and treatment responses, enabling the development of predictive models for oral cancer risk assessment.[21]
- Imaging Data: Medical imaging plays a crucial role in diagnosing and staging oral cancers. Imaging modalities such as X-rays, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and optical coherence tomography (OCT) generate voluminous imaging data that can be analyzed to extract relevant features indicative of the presence, extent, and characteristics of oral cancer.[22]

- Pathological Samples: Histopathological examination of tissue specimens obtained via biopsy or surgical resection provides a definitive diagnosis of oral cancer and insight into tumor histology, grade, and molecular markers. Pathological data, including histopathology slides, immunohistochemistry results, and molecular profiling data, contribute to the development of AI models for oral cancer prediction and characterization.[23]

- Molecular Data: Advances in genomic and molecular profiling technologies have enabled the characterization of oral cancers at the molecular level. Next-generation sequencing (NGS), gene expression profiling, DNA methylation analysis, and proteomic profiling provide insights into the molecular mechanisms underlying oral cancer development and progression, facilitating the identification of biomarkers for risk prediction and treatment stratification.[24]

Data Cleaning and Preprocessing Techniques:

Before analyzing the data, it is essential to preprocess and clean the data to ensure quality, consistency, and suitability for AI modelling. The data cleaning and preprocessing techniques include the following.

- Missing Data Imputation: Missing data are common in clinical datasets and can affect the performance of the AI models. Various imputation methods, such as mean imputation, median imputation, and multiple imputation, are used to fill in missing values while preserving data integrity.[25]

- Outlier Detection and Removal: Outliers or data points that deviate significantly from the rest of the dataset can distort the results of the AI models. Statistical methods, such as z-score analysis and boxplot visualization, are employed to identify and remove outliers or correct them using data transformation techniques.[26]

- Feature Selection and Dimensionality Reduction: Feature selection methods such as correlation analysis, recursive feature elimination, and principal component analysis (PCA) are used to identify the most relevant features for predictive modeling while reducing the dimensionality of the dataset and minimizing overfitting.[27]

- Normalization and Standardization: Normalization and standardization techniques ensure that the values of different features are on a similar scale, preventing bias towards features with larger magnitudes during model training. Common normalization methods include min-max scaling and z-score normalization.[28]

Privacy and Ethical Considerations:

Privacy and ethical considerations are paramount when collecting, storing, and analyzing healthcare data, including oral oncology data. Measures to address privacy and ethical concerns include the following.

- Data Anonymization: Personal health information should be anonymized or de-identified to protect patients' privacy and comply with regulatory requirements such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States.[29] Data anonymization techniques, such as removing direct identifiers (e.g., names, social security numbers) and aggregating data at the group level, help preserve patient confidentiality while enabling data sharing and analysis.[30]

- Informed Consent: Patients provided informed consent for the collection and use of their health data for research purposes, including AI modeling. Informed consent processes should clearly communicate the purpose of data collection, potential risks and benefits, data-handling procedures, and patients' rights regarding data access, sharing, and withdrawal.[31]

- Ethical Oversight: Research involving human subjects, including AI studies in oral oncology, should undergo ethical review by institutional review boards (IRBs) or ethics committees to ensure compliance with ethical principles, protect participants' welfare, and mitigate potential risks. Ethical oversight encompasses considerations, such as beneficence, non-maleficence, autonomy, and justice.[32]
- Data Security: Robust data security measures, including encryption, access controls, audit trails, and secure data transmission protocols, should be implemented to safeguard oral oncology data against unauthorized access, disclosure, alteration, or loss. Data security protocols should adhere to industry standards and regulations to maintain the integrity, confidentiality, and availability of healthcare data.[33]

Machine Learning Techniques for Oral Cancer Prediction

Supervised learning algorithms, a cornerstone of machine learning, leverage labeled data to predict outcomes. In oral cancer prediction, these algorithms, including logistic regression, support vector machines (SVM), and random forests, analyze patient characteristics and imaging data to estimate cancer likelihood. Unsupervised learning techniques, such as k-means clustering and principal component analysis (PCA), uncover hidden patterns in data without explicit labels, aiding in patient subgroup identification and feature extraction. Deep learning, a subset of machine learning, excels in analyzing complex data like medical images and molecular profiles. Convolutional neural networks (CNNs) process medical images to detect tumors, while recurrent neural networks (RNNs) analyze sequential patient data to predict disease progression. Transfer learning further enhances model performance by adapting pre-trained deep learning models to oral cancer datasets with limited labeled data. These diverse techniques offer a comprehensive approach to oral cancer prediction, leveraging advanced algorithms to improve diagnosis and treatment outcomes.

Rahman TY et al. conducted an observational study aiming to propose an automated and efficient computer-aided system capable of distinguishing normal from malignant categories of Oral Squamous Cell Carcinoma (OSCC). The study utilized Convolutional Neural Networks (CNN) for the classification of cell nuclei into normal and malignant categories based on histopathological images derived from 42 slides. Various machine learning models including Decision Tree Classifier, Support Vector Machine (SVM), and Logistic Regression were employed for classification. The study reported impressive accuracy rates, with the decision tree classifier achieving 99.4% accuracy, while both SVM and logistic regression attained 100% accuracy. The in-depth analysis revealed that SVM and linear discriminant classifiers yielded the best results for texture and color features, respectively. The proposed system demonstrated effectiveness, speed, cost-effectiveness, and high accuracy, suggesting its potential utility as an assistant diagnostic tool for physicians in daily clinical screening.[34]

In another study by Rahman et al., the aim was to predict the presence of oral squamous cell carcinoma (OSCC) based on morphological and textural features of hand-cropped cell nuclei using traditional machine learning methods. The study proposed that a structure for semi-automated detection and classification of oral cancer from microscopic biopsy images of OSCC. Clinically significant and biologically interpretable morphological and textural features were examined and proposed. A total of 452 hand-cropped cell nuclei were considered for feature extraction and analysis from 40 biopsy slides. After a comparative analysis of segmentation techniques, a combined technique was proposed, achieving the best segmentation of nuclei. Features extracted were fed into five classifiers: support vector machine, logistic regression, linear discriminant, k-nearest neighbors, and decision tree classifier. Classifiers were also analyzed based on training time. Additionally, the study contributed a large indigenous cell-level dataset of OSCC biopsy images. The study achieved 99.78% accuracy using the decision tree classifier in classifying OSCC based on morphological and textural features.The findings highlight the importance of both morphological and textural features in OSCC diagnosis. The proposed framework holds promise in assisting clinicians and pathologists in OSCC diagnosis.[35]

In the study by Nagarajan et al., a deep learning framework was designed with an intermediate layer between feature extraction layers and classification layers for classifying the histopathological images into two categories, namely, normal and oral squamous cell carcinoma.

The intermediate layer is constructed using the proposed swarm intelligence technique called the Modified Gorilla Troops Optimizer. While many optimization algorithms in the literature are used for feature selection, weight updating, and optimal parameter identification in deep learning models, this work focuses on using optimization algorithms as an intermediate layer to convert extracted features into features better suited for classification. Three datasets comprising 2784 normal and 3632 oral squamous cell carcinoma subjects were considered in this work. Three popular CNN architectures, namely, InceptionV2, MobileNetV3, and EfficientNetB3, were investigated as feature extraction layers. Two fully connected neural network layers, batch normalization, and dropout were used as classification layers.

With the best accuracy of 0.89 among the examined feature extraction models, MobileNetV3 exhibited good performance. This accuracy increased to 0.95 when the suggested Modified Gorilla Troops Optimizer was used as an intermediary layer, demonstrating a significant improvement in prediction accuracy for identifying oral squamous cell carcinoma.[36]

Ahmad et al. employed several artificial intelligence techniques to predict oral squamous cell carcinoma (OSCC) and aid clinicians or physicians, thereby significantly reducing the workload of pathologists. Their study aimed to develop hybrid methodologies based on fused features to generate better results for the early diagnosis of OSCC. The researchers employed three different strategies, each using five distinct models. The first strategy involved transfer learning using the Xception, Inceptionv3, InceptionResNetV2, NASNetLarge, and DenseNet201 models. In the second strategy, they utilized a pre-trained convolutional neural network (CNN) for feature extraction combined with a Support Vector Machine (SVM) for classification. Specifically, features were extracted using various pre-trained models, namely Xception, Inceptionv3, InceptionResNetV2, NASNetLarge, and DenseNet201, and subsequently applied to the SVM algorithm to evaluate the classification accuracy. The final strategy employed a cutting-edge hybrid feature fusion technique, utilizing an art-of-CNN model to extract deep features from the aforementioned models. These deep features underwent dimensionality reduction through principal component analysis (PCA). Subsequently, low-dimensionality features were combined with shape, color, and texture features extracted using gray-level co-occurrence matrix (GLCM), Histogram of Oriented Gradient (HOG), and Local Binary Pattern (LBP) methods. Hybrid feature fusion was incorporated into the SVM to enhance the classification performance. The proposed system achieved promising results for the rapid diagnosis of OSCC using histological images. The accuracy, precision, sensitivity, specificity, F-1 score, and area under the curve (AUC) of the support vector machine (SVM) algorithm based on the hybrid feature fusion of DenseNet201 with GLCM, HOG, and LBP features were 97.00%, 96.77%, 90.90%, 98.92%, 93.74%, and 96.80%, respectively.[37]

The table 2 summarizes the key studies, algorithms used, metrics evaluated, and key findings related to the prediction of oral squamous cell carcinoma using artificial intelligence techniques.

Performance Evaluation and Validation

Metrics for Assessing Prediction Models (Table 3):

Evaluating the performance of prediction models is essential for assessing their effectiveness and generalization capabilities. Several metrics are typically used to quantify the performance of oral cancer prediction models.

- Sensitivity and Specificity: Sensitivity (true positive rate) measures the proportion of actual positive cases correctly identified by the model, while specificity (true negative rate) measures the proportion of actual negative cases correctly identified by the model. These metrics assess the model's ability to detect true positives (oral cancer cases) and true negatives (non-cancer cases).[38]
- Accuracy: Accuracy measures the overall correctness of the predictions made by the model, calculated as the ratio of correctly predicted cases to the total number of cases. While accuracy provides a comprehensive view of model performance, it may be misleading in imbalanced datasets where classes are unevenly distributed.[38]
- Area Under the Receiver Operating Characteristic Curve (AUC-ROC): The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) for different threshold values, whereas the AUC-ROC quantifies the overall discriminative power of the model across all possible threshold values. A higher AUC-ROC indicates a better discrimination between positive and negative cases.[39]
- Precision and Recall: Precision measures the proportion of true positive predictions among all positive predictions made by the model, whereas recall (also known as sensitivity) measures the proportion of true positive predictions among all actual positive cases. Precision and recall provide insights into the model's performance in correctly identifying positive cases and minimizing false-positive predictions.

- F1 Score: The F1 score is the harmonic mean of the precision and recall, providing a balanced measure of the model's performance in terms of both false positives and false negatives. This is particularly useful in imbalanced datasets, where the classes are unevenly distributed.[40]

The studies presented in Table 4 offer a comprehensive overview of the application of AI-based models in oral cancer detection, diagnosis, classification, and prediction using histopathological images. These studies have employed various deep learning architectures, including convolutional neural networks (CNNs), capsule networks, and artificial neural networks (ANNs), to develop computer-aided diagnostic systems for oral squamous cell carcinoma (OSCC). The findings from these studies underscore the transformative potential of AI-based models in improving the accuracy, efficiency, and prognostic value of oral cancer diagnosis and management. By leveraging deep learning techniques, these models offer valuable tools for pathologists and clinicians to enhance diagnostic accuracy, facilitate early detection, and personalize treatment strategies for OSCC patients. However, further validation and clinical integration of these AI systems are warranted to realize their full potential in routine clinical practice. Additionally, future research should focus on developing standardized protocols, addressing data heterogeneity issues, and conducting large-scale clinical trials to validate the efficacy and generalizability of AI-based diagnostic systems for oral cancer.[41]

Cross-Validation Techniques (Table 5):

Cross-validation is a robust technique used to assess the performance and generalization of prediction models by partitioning a dataset into multiple subsets for training and evaluation. Common cross-validation techniques include the following.

- K-Fold Cross-Validation: In K-fold cross-validation, the dataset was divided into K equal-sized folds. The model was trained K times, each time using K-1 folds for training and the remaining fold for validation. The performance metrics were averaged across all K iterations to obtain an overall estimate of the model performance.[42]

- Leave-One-Out Cross-Validation (LOOCV): In LOOCV, each sample in the dataset is used as a validation set once, and the remaining samples are used for training. LOOCV provides a rigorous evaluation of model performance, but may be computationally expensive for large datasets.[43]
- Stratified Cross-Validation: Stratified cross-validation ensures that each fold maintains the same class distribution as the original dataset, thereby preserving the balance between positive and negative cases. This is particularly important in imbalanced datasets to prevent biased evaluation of the model performance.[44]
- Shuffle-Split Cross-Validation: Shuffle-split cross-validation randomly shuffles a dataset and splits it into training and validation sets multiple times. This technique is useful for large datasets and provides flexibility in controlling the size of the training and validation sets.[45]

Clinical Validation and Real-world Implementation:

Clinical validation involves the assessment of the performance of prediction models in real-world clinical settings to evaluate their utility and impact on patient care. Clinical validation studies typically involve the following steps:

- Prospective Cohort Studies: Prospective cohort studies recruited patients with suspected or confirmed oral cancer and applied a prediction model to prospectively collect data on model performance, diagnostic accuracy, and clinical outcomes. These studies provided valuable insights into the model's performance in real-world clinical practice.[46]

- External Validation: External validation involves testing the prediction model on an independent dataset collected from a different population or clinical setting to assess its generalizability and robustness across diverse patient cohorts. External validation ensures that the performance of the model is not limited to the training dataset and can be applied to new patient populations with similar characteristics.[47]
- Clinical Impact Assessment: Assessing the clinical impact of prediction models involves evaluating their influence on clinical decision making, patient outcomes, healthcare resource utilization, and cost-effectiveness. Clinical impact studies quantify the benefits of implementing the prediction model in routine clinical practice and guide healthcare providers in incorporating the model into clinical workflows.[48]
- Regulatory Approval: Prediction models intended for clinical use may require regulatory approval from government agencies such as the Food and Drug Administration (FDA) in the United States or the European Medicines Agency (EMA) in Europe. Regulatory approval ensures that the prediction model meets the safety, efficacy, and quality standards for use in clinical practice and patient care.[49]

Challenges and Future Directions

Interpretability and Transparency:

One of the primary challenges in applying AI to oral oncology prediction is the lack of interpretability and transparency of complex AI models. Deep learning algorithms, in particular, are often considered "black box" models, making it difficult to understand how they arrive at specific predictions.[50] Addressing the development of interpretable AI models that provide clinicians with insights into the features and patterns driving predictions. Techniques, such as feature importance analysis, attention mechanisms, and model visualization, can enhance the interpretability of AI models and foster trust and acceptance among healthcare providers.

Data Accessibility and Quality:

Access to high-quality data is essential for training robust and generalizable AI models in the prediction of oral oncology. However, obtaining labeled datasets for model training can be challenging owing to issues such as data privacy, heterogeneity, and scarcity. Future efforts should focus on improving data accessibility through data sharing initiatives, collaboration among healthcare institutions, and standardized data collection protocols.[51] Additionally, ensuring data quality through rigorous data curation, annotation, and validation processes is critical to enhancing the reliability and performance of AI models in oral oncology prediction.[52]

Regulatory and Legal Implications:

Adhering to reporting guidelines is crucial for the transparency and reliability of AI applications in medicine. Notable guidelines include:

- **TRIPOD+AI:** An extension of the TRIPOD statement, tailored for AI prediction models.[53]
- **DECIDE-AI:** A framework for the design and reporting of early-stage clinical evaluation of AI-based decision-making technologies.[54]

Potential Impact on Oral Oncology Care:

Despite these challenges, AI has the potential to revolutionize oral oncology care by enhancing early detection, diagnosis, prognosis, and treatment decision making. AI-powered prediction models can assist clinicians in identifying high-risk individuals for targeted screening and surveillance, optimizing treatment strategies based on personalized risk profiles, and improving patient outcomes through timely interventions and precision medicine approaches.[52,55]

Furthermore, AI-driven insights derived from large-scale data analysis can accelerate scientific discovery, identify novel biomarkers and therapeutic targets, and inform clinical trial design and drug development efforts in oral oncology.[56] By harnessing the transformative potential of AI, oral oncology care can transition towards a more patient centered, data-driven, and precision-oriented approach, ultimately improving the quality of care and outcomes for patients with oral cancer.[57]

Conclusion and Outlook

In conclusion, the application of artificial intelligence (AI) in oral oncology prediction holds great promise for improving early detection, diagnosis, and treatment outcomes for patients with oral cancer. Through the integration of diverse data sources, including clinical records, imaging data, pathological samples, and molecular profiles, AI-driven prediction models can accurately assess individualized risks, guide clinical decision-making, and inform personalized treatment strategies. Supervised and unsupervised learning algorithms as well as deep learning approaches play a pivotal role in analyzing complex oral cancer data and extracting meaningful insights for risk assessment, prognosis, and therapeutic interventions. However, several challenges, including interpretability, data accessibility, regulatory compliance, and legal considerations, must be addressed to realize the full potential of AI in oral oncology prediction.

Future Prospects and Research Directions:

Future research on AI for oral oncology prediction should focus on addressing the aforementioned challenges and advancing the field in several key areas. This includes developing interpretable AI models that provide clinicians with actionable insights and decision support tools; enhancing data accessibility and quality through collaborative efforts and data-sharing initiatives; navigating the regulatory and legal landscape to ensure compliance and ethical use of AI in healthcare; and exploring innovative AI-driven approaches, such as federated learning and explainable AI, to improve model performance and transparency. Moreover, integrating AI with emerging technologies such as genomics, proteomics, and digital health platforms offers exciting opportunities for precision oncology and personalized patient care in oral cancer.

Implications for Clinical Practice:

The adoption of AI in clinical practice has profound implications for oral oncology care by reshaping workflows, decision-making processes, and patient outcomes. AI-powered prediction models can assist healthcare providers in identifying individuals at a high risk of oral cancer development, facilitating early detection and intervention to improve survival rates and quality of life. Moreover, AI-driven decision support systems can optimize treatment planning and monitoring, guiding clinicians in selecting the most effective therapies based on individual patient characteristics and tumour biology. By harnessing the predictive power of AI, oral oncology care can transition towards a more proactive, personalized, and evidence-based approach, ultimately leading to better patient outcomes and reducing the burden of oral cancer morbidity and mortality.

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Tables

Table 1: AI Algorithms and Their Classes

Class	Algorithm Examples	Application
Supervised ML[58]	SVM, Random Forest, Logistic Regression	Classification, Regression
Unsupervised ML[59]	K-means, PCA	Clustering, Dimensionality Reduction
Deep Learning	CNN, RNN, LSTM	Image Analysis, Sequential Data Analysis
NLP[60]	NER, Sentiment Analysis, Text Classification	Text Analysis

Table 2: Algorithms used, metrics evaluated, and key findings related to the prediction of oral squamous cell carcinoma using artificial intelligence techniques.

Study	Algorithm	Metrics Used	Key Findings
Rahman TY et al.[34]	Convolutional Neural Networks (CNN), Decision Tree Classifier, Support Vector Machine (SVM), Logistic Regression	Accuracy	Decision tree classifier achieved 99.4% accuracy, SVM and logistic regression attained 100% accuracy. SVM and linear discriminant classifiers yielded the best results for texture and color features, respectively. Proposed system demonstrated effectiveness, speed, cost-effectiveness, and high accuracy.

Rahman et al.[35]	Support Vector Machine (SVM), Logistic Regression, Linear Discriminant, k-Nearest Neighbors, Decision Tree Classifier	Accuracy	Achieved 99.78% accuracy using the decision tree classifier in classifying oral squamous cell carcinoma (OSCC) based on morphological and textural features.
Nagarajan et al.[36]	Modified Gorilla Troops Optimizer as intermediate layer, InceptionV2, MobileNetV3, EfficientNetB3	Accuracy	MobileNetV3 exhibited 89% accuracy; 95% accuracy when Modified Gorilla Troops Optimizer used as an intermediary layer.
Ahmad et al.[37]	Xception, Inceptionv3, InceptionResNetV2, NASNetLarge, DenseNet201, Support Vector Machine (SVM)	Accuracy, Precision, Sensitivity, Specificity, F-1 Score, AUC	Achieved 97.00% accuracy, 96.77% precision, 90.90% sensitivity, 98.92% specificity, 93.74% F-1 score, and 96.80% AUC using hybrid feature fusion of DenseNet201 with GLCM, HOG, and LBP features.

Table 3: Performance Metrics for Oral Cancer Prediction Models[61-62]

Metric	**Description**
Sensitivity	Proportion of true positive cases correctly identified by the model
Specificity	Proportion of true negative cases correctly identified by the model
Accuracy	Overall correctness of predictions made by the model
AUC-ROC	Area under the receiver operating characteristic curve
Precision	Proportion of true positive predictions among all positive predictions made by the model
Recall	Proportion of true positive predictions among all actual positive cases
F1 Score	Harmonic mean of precision and recall

Table 4: Overview of the studies, highlighting the key information of AI-based models in oral cancers

Authors and Year	Study Design	Algorithm Architecture	Objective of the Study	Outcomes
Lu C et al.[63] (2017)	Observational	CNN	Oral cavity histomorphometric-based image classifier for OSCC risk stratification	ROC: 0.72 (Effective)
Das DK et al.[64] (2018)	Observational	CNN	Identify relevant regions from oral tissue histological images	Segmentation accuracy: 98.42% (Effective)
Das DK et al.[65] (2019)	Observational	CNN	Develop computational pipeline for nucleus detection from histology images	Dice coefficient: 94.22% (Effective)
Rahman TY et al.[34] (2019)	Observational	CNN	Develop CAD system for OSCC classification using textural features	Accuracy: 100% (Effective)
Shaban M et al.[66] (2019)	Observational	CNN	Automated TIL abundance score and its prognostic significance for OSCC	Accuracy: 96.31% (Effective)
Das N et al.[67] (2020)	Observational	CNN	Classify OSCC into Broder's grading classes	Accuracy: 97.5% (Effective)
Fraz MM et al.[68] (2020)	Observational	CNN	Simultaneous segmentation of microvessels and nerves in histology images	Accuracies: 96.3% for nerves, 97.05% for blood vessels (Effective)
Martino F et al.[69] (2020)	Observational	SSNs	Compare deep learning-based architectures for oral cancer segmentation	mIOU: 0.63 (Effective)
Amin I et al.[70] (2021)	Observational	CNN	Automated classification of cancerous oral histopathological images	Accuracy: 96.66% (Effective)
Rahman TY et al.[35] (2021)	Observational	CNN	Distinguish normal from malignant OSCC categories using CAD system	Accuracy: 100% (Effective)
Panigrahi S et al.[71] (2022)	Observational	CNN	Multistage classification of OSCC	Accuracy: 97.59% (Effective)

			into benign and malignant	
Panigrahi S et al.[72] (2022)	Observational	Capsule network	Classification of oral cancer using capsule network	Sensitivity: 97.78%, Specificity: 96.92%, Accuracy: 97.35% (Effective)
Deif MA et al.[73](2022)	Observational	CNN	Diagnose OSCC using deep neural networks	Accuracy: 96.3% (Effective)
Yang SY et al.[74] (2022)	Observational	CNN	Develop deep learning model for OSCC detection from histopathology images	Sensitivity: 0.98, Specificity: 0.92 (Effective)
Yoshizawa K et al.[75](2022)	Observational	CNN	Determine mode of invasion based on digital images of OSCC invasive front	F-measure value: 87% (Effective)
Fati SM et al.[76] (2022)	Observational	CNN, ANN	Hybrid techniques for early diagnosis of OSCC using fused features	Accuracy: 99.3% (Effective)

Footnotes: AUC = area under the curve; CNNs = convolutional neural networks; DWT = discrete wavelet transform; FCH = fuzzy color histogram; GLCM = gray level co-occurrence matrix; IHC = immunohistochemical; LBP = local binary pattern; mIOU = mean intersection-over-union; OSCC = oral squamous cell carcinoma; ROC = receiver operating characteristic curve; SNNs = semantic segmentation deep neural networks; TIL = tumor infiltrating lymphocytes.

Table 5: Cross-Validation Techniques for Model Evaluation[42,77]

Technique	Description
K-Fold Cross-Validation	Divides the dataset into K folds for training and evaluation
Leave-One-Out Cross-Validation	Uses each sample as a validation set once, with the remaining samples used for training
Stratified Cross-Validation	Ensures each fold maintains the same class distribution as the original dataset
Shuffle-Split Cross-Validation	Randomly shuffles the dataset and splits it into training and validation sets multiple times

Highlights

1. AI enhances oral cancer prediction: early detection, personalized treatment, improved outcomes.
2. Challenges: data quality, interpretability, legal compliance.
3. Future: interpretable models, collaborative data sharing, regulatory alignment.
4. Clinical impact: proactive risk assessment, personalized therapy, better patient care.
5. AI revolutionizes oral oncology: precision medicine, data-driven decision-making.

Declaration of interests

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: