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Review Article

Precision and speed: The AI revolution in oral squamous cell carcinoma detection

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A B S T R A C T

Oral Squamous Cell Carcinoma (OSCC) is a highly aggressive tumor with a poor prognosis and is most frequent histological neoplasm of head and neck cancers, and although it is localized in a region that is accessible to see and can be detected very early, this usually does not occur. The standard procedure for the diagnosis of oral cancer is based on histopathological examination, however, the main problem in this kind of procedure is tumor heterogeneity where a subjective component of the examination could directly impact patient-specific treatment intervention. AI can precisely analyze a vast dataset of various imaging modalities, such as fluorescent, hyperspectral, cytological, histological, radiological, endoscopic, clinical, and infrared thermal modalities. In this review, we discuss digital histopathological image analysis, computer vision and radiological analysis for the early detection of OSCC.

1. Introduction

Oral squamous cell carcinoma (OSCC) remains a leading cause of cancer-related deaths, with approximately 170,000 fatalities each year, largely due to late-stage diagnosis. The average age of diagnosis is 66 in women and 62 in men. Early detection and screening are vital for improving survival rates, as the stage of cancer at diagnosis significantly impacts patient outcomes.

In recent years, the integration of artificial intelligence (AI) and computer vision has transformed medical diagnostics. These technologies offer great potential for enhancing the accuracy and speed of oral cancer detection through the analysis of digitized oral images. Oral cancer is a major global health issue, often going undetected until advanced stages, which results in lower survival rates. However, advancements in machine learning and image analysis are driving significant changes in how oral cancer is diagnosed.

This literature review will focus on the detection of oral cancer through photographic images, digital histopathology, and radiographic methods.

The review critically evaluates current research that applies AI and computer vision to improve oral cancer detection. By analyzing and synthesising key studies, methodologies, and findings, this paper aims to provide a comprehensive overview of the progress at the intersection of medicine and computer science. The goal is to highlight the emerging role of machine vision in shaping the future of oral cancer diagnosis.[1]

2. Discussion

Oral squamous cell carcinoma (OSCC) is defined by the uncontrolled and chaotic growth of epithelial cells, which leads to rapid expansion and local tissue destruction. OSCC may or may not involve distant spread and metastasis, depending on the stage. Epidermoid carcinoma makes up

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90% of malignant tumours in the oral cavity.[2]

Artificial intelligence (AI) includes a broad spectrum of techniques and technologies designed to create systems that mimic human cognitive functions such as reasoning, problem-solving, perception, and language understanding.

To achieve this, AI systems gather information from inputs or past data through various AI subsets, including machine learning (ML), neural networks (NN), and deep learning (DL). ML, a key component of AI, involves the development of computational algorithms that enable a computer system to learn from a predefined dataset. ML methods are classified based on the availability of training data, the algorithmic process, and the applied segmentation model, with the most common types being supervised learning (where the data is pre-labeled by the operator), unsupervised learning (where the data is unlabeled), and semi-supervised learning (which uses both labeled and unlabelled data). Deep learning (DL), a subfield of AI based on neural networks (NN), utilises artificial networks composed of multiple interconnected layers of neurons. DL employs complex models that surpass the capabilities of traditional machine learning tools like logistic regression and support vector machines. It is beneficial to examine various learning tasks, including supervised, unsupervised, semi-supervised (hybrid), and reinforcement learning.[3]

3. Computer Methods

Computer vision, a subfield of AI, aims to enable machines to interpret and understand visual information from the world. It involves developing algorithms and techniques that allow computers to analyse, process, and comprehend images or videos.

Neural networks are a captivating type of machine learning algorithms inspired by the human brain's intricate workings. These networks consist of interconnected nodes that perform simple mathematical operations, collectively identifying patterns from large datasets during training.

Back propagation is a key training algorithm that empowers neural networks. It calculates errors and systematically adjusts weights based on the network's output, refining the model's capabilities. This iterative process continues until the neural network can generate accurate outputs for various inputs.

In image analysis, Convolutional Neural Networks (CNNs) play a crucial role. CNNs are specialised neural networks designed for processing grid-like data, such as images. They use specialised layers to automatically and adaptively extract features from input images, enabling the identification of complex patterns in medical imagery, which is essential for accurate cancer detection and analysis.[1]

A typical Convolutional Neural Network (CNN) consists of input and output layers, along with key layers such as convolution, max pooling, and fully connected layers. These layers are crucial for progressively learning abstract features from input data, such as images. When an image is fed into a CNN, the convolution layer extracts features from the input, which are then processed further in the pooling layers. Finally, the reduced feature maps are passed into the fully connected layer to classify the images into their respective labels. CNNs have become valuable in medical applications due to their ability to overcome the limitations of traditional fully connected layers, such as computational inefficiencies. Over time, several CNN architectures have been developed, including LeNet, AlexNet, DenseNet, GoogLeNet, ResNet, and VGGNet. Despite the differences between these models, their core principles remain largely the same.[4]

One significant advantage of CNNs is their ability to extract image features and generalise across various computer vision problems. However, their effectiveness depends on substantial labeled data, and they have high computational demands.

The literature shows that most researchers have applied CNNs in retrospective studies to detect and classify oral cancer. It is noted that many of these classification tasks were binary, using image features such as colour, shape, and texture. Although CNNs are powerful models for image recognition, some researchers employed deep CNNs, which outperform conventional CNNs in classification tasks.

Chan et al. proposed an innovative deep CNN combined with a texture map for oral cancer detection. Their model consists of two collaborative branches: one for oral cancer detection and another for region of interest (ROI) marking and semantic segmentation.[1]

Transfer learning is another powerful strategy in neural network training. It involves applying knowledge gained from training one model on a specific task to a related task. This approach can significantly speed up training and improve performance, especially when datasets for the new task are limited.

Attention mechanisms, which mimic cognitive attention, focus on relevant aspects of the input, highlighting critical elements while fading out less important ones. Though relatively new in the field of medical imaging, attention mechanisms require substantial training data and are computationally intensive.

In image analysis tasks, classification involves identifying the type of object within an image by predicting a semantic label, detection entails pinpointing the presence and position of objects in an image, and segmentation involves identifying pixels associated with each object in the image. Each task adds a layer of sophistication to the network's understanding and utilisation of complex data structures.

All the research papers utilised transfer learning with pre-existing models, retraining them on oral cancer images. The best-performing model among them was VGG-19. VGG, a simpler type of CNN, generalises well to various tasks. On the other hand, ResNet, which uses skip connections to relieve the vanishing gradient problem and facilitate training of very deep networks, requires more data and is therefore not the best fit for this specific task.

In summary, the most promising machine learning approaches used by the authors are:

1. Texture descriptor: These features, which describe the spatial arrangement of pixels, have proven effective in classifying oral cancer cells by capturing subtle texture changes associated with cancer.
2. Attention model: These neural networks can learn to focus on specific regions of an image, which is useful for oral cancer detection as it allows the model to disregard irrelevant information and concentrate on the most critical features for classification.
3. Localisation with multi-task learning: These two machine learning techniques are used jointly in this study. Localisation identifies the location of a specific object in an image, while multi-task learning enables a model to learn multiple tasks simultaneously. Their combined usage has shown promise.
4. Ensemble approach: This technique combines predictions from multiple models to enhance overall performance, reducing the risk of overfitting and increasing the model's robustness in oral cancer detection.
5. Data augmentation: This artificially increases the dataset's size by generating new data from existing samples, improving the model's ability to generalise and detect oral cancer more accurately.[5]

4. Promising Machine Learning Approaches

Several promising machine learning approaches have emerged to enhance the detection of oral cancer. One such approach is the use of attention mechanisms, which, though still in the early stages of research, show great potential. A recent study incorporating attention mechanisms demonstrated how focusing computational resources on relevant image regions can significantly improve detection accuracy. Furthermore, new research suggests that attention models or transformers, which typically require large datasets, can also be trained effectively on smaller datasets.

Ensemble learning has also shown considerable promise. A notable example achieved an impressive accuracy rate of 96.2%, demonstrating the power of combining multiple models to enhance classification. This method leverages the diversity of individual models to make robust predictions, even with limited data.

Additionally, image enhancement techniques have emerged as an effective way to boost detection accuracy. Despite being applied to smaller datasets, these techniques have improved image quality and, in turn, model performance.

Landmark detection is another intriguing approach that uses anatomical landmarks to guide the detection process. When combined with multi-task learning, this technique improves the precision of cancer detection, enabling more accurate and targeted diagnoses. Among various architecture options, VGG-19 has consistently performed the best in multiple studies. Its ability to extract complex features from images makes it particularly well-suited for oral cancer detection, contributing to the high accuracy rates observed.[1]

5. Histopathological Methods

Histopathological analysis of tissue biopsies by an oral pathologist remains the gold standard for diagnosing OSCC. The advent of slide digital scanners has revolutionised tissue histopathology, offering several advantages, including the ability to apply computerised image analysis and machine learning (ML) techniques. These algorithms are now being developed for research, disease detection, diagnosis, and prognosis prediction, serving to enhance the pathologist's perspective. The objective characterisation and pattern recognition of tissues and structures in digital slides are crucial not only for diagnostic purposes but also for understanding the biological mechanisms underlying the pathological process, which is valuable for research. We briefly explore the emerging applications of digital histopathological image analysis in OSCC.

Deep learning (DL) is a subset of AI that utilises artificial neural networks (NN) composed of input and output data. In digital pathology, an important DL technique for image analysis is image segmentation. Image segmentation involves dividing a whole slide image (WSI) into multiple parts to isolate and cluster images or objects of interest based on their optical properties. The use of WSI enables the analysis and enhancement of high-resolution, high-quality images, which aids in the visualisation of stained tissue slides and allows for the sharing of cases between oral pathologists.

5.1. Digital image analysis

The commonly used image processing and analysis software is ImageJ 1.53t©, an open-access tool designed for the study of multidimensional images. This software also serves as the foundation for FIJI 1.53t©, another widely available open-access program. ImageJ is highly regarded for its practicality, reproducibility, impartiality, and efficiency, largely due to the continuous development and sharing of tools called plugins by the scientific community. Plugins are specialised software components designed for specific tasks such as colour deconvolution, cell counting, colour segmentation, and watershed transformation, among others.

These tools are designed to assist pathologists and clinicians in decision-making processes, helping to reduce diagnosis delays and errors, ultimately promoting patient health.

According to Alabi et al., machine learning (ML) applications in oral cancer cover a wide range of areas, from combining clinical, pathological, and genomic data to analysing images and autofluorescence information. They found that deep neural networks (NN) are among the most widely used approaches for oral cancer analysis. Deep NNs, inspired by the human brain, process information layer by layer, extracting and labelling relevant data to classify new information. However, despite the precision and objectivity of these models, the authors noted that achieving accurate diagnosis and prognosis remains challenging, with limited real-world contributions to the medical field. One issue is that algorithms are often tailored to specific tissue types, making it difficult to generalise the methods to other tissues with different characteristics. Additionally, studies can be constrained by the limited number of images available, making it difficult to obtain sufficient datasets for training and testing.

5.2. *Whole slide images*

The use of whole slide images (WSI) in pathology offers numerous advantages. WSI allows entire tissue sections on glass slides to be transformed into digital, high-resolution virtual slides. In this context, WSI is a valuable tool for applying various AI algorithms in both diagnostic and research settings. Compared to traditional techniques like optical microscopy, WSI offers several benefits, including the integration of AI, preservation of the quality of staining techniques used on the tissue, and the ability to easily share digitised slides with pathologists around the world.

5.3. *Current applications of whole slide images in AI for SCC*

Recent studies have increasingly applied digital images, particularly whole slide images (WSI), to implement AI methods for various approaches in head and neck squamous cell carcinoma (HNSCC). These methodologies offer the advantage of automated quantification in WSIs of tissue slides, which leads to more robust analyses and reduces operator bias.

As illustrated, digital pathology advancements, particularly in using WSIs, offer numerous advantages. Digitized files enable pathologists worldwide to engage in digital capture, storage, sharing, visualization, and the application of advanced techniques for various analyses through specialized software. Additionally, the long-term preservation and storage capacity of digital files present further benefits, making this technology a promising candidate for short-term implementation in pathology centres.

5.4. *Image segmentation*

Automatic segmentation of digitized histological images into regions representing different tissue types is crucial for developing digital tools for diagnosis, prognosis, and therapy. Segmentation is a computational technique that processes digital images by grouping pixels with similar colorimetric properties into regions likely representing objects of interest, such as cells, vessels, and other tissue structures. These regions can then be geometrically characterized to obtain both qualitative and quantitative information about the objects they represent. The most commonly used software for this purpose includes ImageJ and FIJI, which continuously evolve with new plugins and tools to achieve specific goals. Techniques like thresholding, StarDist, watershed transform, trainable WEKA segmentation, and Labkit are among those used for image segmentation.

Pattern recognition techniques offer another approach to segmentation, where certain characteristics like colour, shape, and size are selected, and results are clustered into regions corresponding to histological classes. Many methods applied to histopathological images stained with H&E, immunohistochemistry, and histochemical procedures rely on thresholding, which starts with a threshold value of colour or intensity to identify the object of interest. In this process, thresholding groups pixels based on shared characteristics, resulting in a binary image where the object of interest and the background are distinguished by values of 1 or 0. This technique is part of a more complex process that allows pathologists to determine the presence or absence of specific components in tissue samples,

A relatively new segmentation technique based on deep learning (DL) and neural networks (NN) is StarDist, developed in Germany in 2018. StarDist detects cell nuclei by predicting their morphological profiles and is flexible and precise enough to compete with other segmentation methods. It uses a star-convex-polygon shape to approximate the round morphology of nuclei. This innovative model is applicable not only to histological H&E images but also to fluorescent nuclei detection. By defining nuclei morphology, StarDist enables the study of various nuclear parameters, including nuclear density and condensation.

The watershed transform is a morphological segmentation technique that divides objects of interest by creating watershed lines within catchment basins, effectively constructing three-dimensional topographic maps where intensity represents altitude. This method simulates water immersion, with watershed lines forming where different catchment basins meet. In histopathology, this technique uses nuclear location and intensity to segment tissues into virtual cells (v-cells), allowing for the analysis of cellular and layer morphology. To apply this plugin, images must be in 8-bit binary format (with values of 0 and 255), and the segmented areas will have a white background.

Trainable WEKA (Waikato Environment for Knowledge Analysis, developed in New Zealand in 2009) and Labkit (Labeling and Segmentation Toolkit for Big Image Data, developed in Germany) are two open-source software tools that integrate FIJI, machine learning (ML), and random forest (RF) algorithms to segment and classify pixels. To use these tools, the operator must first label the objects of interest that the software is intended to recognize. These labeled examples are then used to train the model, which can subsequently classify new images. This approach enables the segmentation of histological images to identify structural components, ranging from epithelial and connective layers to nuclei, basal membranes, cells, and vessels. Additionally, these techniques can differentiate images based on staining, such as segmenting objects stained with immunohistochemistry from backgrounds stained with Mayer's hematoxylin.

5.5. *Comparing data results*

One challenge in AI procedures is the comparison of results across different samples. For accurate comparisons, pathologists should adhere to the same protocol, including factors like magnification, resolution, image size, and standardized staining procedures. However, this can introduce bias, particularly if the same dataset is used for both model selection and evaluation. To mitigate bias, Mahmood et al. recommend dividing the dataset into three distinct groups: one for model training, one for optimal model selection, and one for model validation, while also adding new data to the latter two groups. Additionally, the authors suggest incorporating samples from various pathology centers to enhance diversity and account for biological variations across different demographics.

Supervised training techniques, which require human annotation to train segmentation models, should involve multiple pathologists to minimize subjectivity and reduce inter-pathologist variation. When standardization of sample handling is not possible, pre-processing images can help; adjusting contrast, reducing noise, and using filters can better delineate structures and differentiate tissues, facilitating image standardization and enabling more reliable comparisons.[3]

5.6. *Future perspectives and limitations*

The field of oncology has made significant progress with the incorporation of deep learning algorithms. These intelligent systems assist pathologists in effectively classifying cancer across multiple categories, thereby empowering the oncology team to chart out a treatment module, reducing the operational workload and enhancing disease management. Moreover, deep learning models allow clinicians to classify patients into different risk categories for determining the most suitable treatment.

This approach could spare those who do not fall into the high-risk bracket from the more unpleasant side effects of intensive treatments. However, while this has the potential to pave the way for AI to be widely implemented, data privacy and confidentiality remain obstacles in applying AI to clinical oncology. Of particular concerns are the potential interpretation errors that could arise while relying heavily on software for medical diagnoses and who should bear ultimate responsibility—the digital intelligence or the skilled doctor. Additionally, AI's introduction into oncology practice has the potential to impact the patient–doctor relationship and the patient's autonomy. AI models are designed to assist pathologists and clinicians in clinical decision making. These models have demonstrated outstanding results in performing these tasks. However, when there is discordance between the AI models and the human experts, the latter make the final decision based on their clinical expertise. AI models developed for application in histopathological diagnosis are based on ML and DL, which are subsets of AI. DL models are easy to use in comparison to ML models and have better accuracy, as they are suitable for large sets of data. Moreover, the input of the defined features is not required, as their performance continues to improve with more practice. DL models have an added advantage due to their ability to work on unstructured data and to generate new features with higher quality from datasets without human interventions, which improves their accuracy in diagnosis.

One of the limitations of these AI applications is the problem of the interpretability and explainability of the operation of these algorithms. AI models should provide clinicians and patients with a complete understanding of their decisions. However, to date, there has been no unified method for evaluating interpretability. All of these concerns require careful consideration in order to arrive at an appropriate solution.[6]

5.7. *Advances in oral cancer research*

Effective diagnosis and prognosis of oral cancer using AI require a thorough understanding of cancerous tissues and the identification of distinguishing parameters. Research has explored various aspects, including keratinization and keratin pearl areas, stage differentiation through linear layer neural network classifiers and hyperspectral imaging, cell nuclei segmentation, immunohistochemical biomarkers, and textural, shape, and color features. This section highlights recent advances in AI applications specific to OSCC.

Pratama et al. investigated classifying OSCC from different sites using RNA sequencing data and CNNs, but found limited success in differentiating histopathological features. Conversely, Santer et al. applied ML and DL to classify cervical lymph nodes in locally advanced OSCC, achieving an 86% accuracy rate in both training and testing sets, suggesting the potential of quantitative AI as a diagnostic aid.

Das et al. used 1,224 histopathological images (290 normal and 934 cancerous) to differentiate OSCC from normal tissue, employing CNNs. This deep learning approach achieved 82% accuracy, indicating its viability as an automated tool for oral cancer detection. Yang et al. developed a custom DL model that enhanced both the accuracy and speed of OSCC diagnosis. Rahman et al. utilized transfer learning with AlexNet in a CNN to predict oral cancer from biopsy images, attaining 90.06% accuracy based on various performance metrics. The authors suggested that further collaboration could refine this model.

Regarding survival prediction for oral cancer patients, Kim et al. compared a DL-based survival prediction method (DeepSurv) with traditional statistical methods in a retrospective study of 225 patients. DeepSurv showed superior performance as measured by Harrell's c-index. Similarly, Tseng et al. created a model for predicting 5-year disease-free and disease-specific survival rates using data mining, finding that decision tree and ANN methods outperformed traditional logistic regression. These studies indicate that AI could enhance prognosis prediction, although additional research is needed.

5.8. Role of AI in immunofluorescence and immunohistochemistry for oral cancer

Immunohistochemistry and immunofluorescence are well-established techniques for studying oral cancer behavior. Quantitative digital analysis of biomarker expression aids in understanding their implications in pathological images. Kawamura et al. analyzed the expression of various biomarkers in 1,854 images from 76 OSCC patients using a multilayer perceptron neural network, achieving 98.6% accuracy in assessing staining levels and correlating with cervical lymph node metastasis.

Multiplex immunofluorescence imaging to predict combined positive scores for markers like PD-L1 has been explored using DL and ML techniques. Manual scoring of PD-L1 expression on at least 100 tumor cells is labor-intensive and subjective. AI approaches increase the efficiency of tumor analysis and improve the likelihood of identifying responsiveness to immunotherapies. Tsakiroglou et al. used DL and CNNs to process and segment PD-L1 immunofluorescence staining in oropharyngeal squamous cell carcinomas with QuPath software, offering a new tool for supporting diagnosis and targeting the PD-1/PD-L1 immune escape pathway.[3]

6. Radiographic Methods

Conventional visual examinations in clinical settings are not reliable predictors for diagnosing oral cancer, highlighting the need for a quantitatively validated diagnostic method. While radiographic imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT) can assess the size and extent of oral cancer before treatment, they are not sensitive enough to detect precancerous lesions. Consequently, various adjunct clinical imaging techniques, including autofluorescence and optical coherence tomography (OCT), have been explored.

Artificial intelligence (AI) has been increasingly applied across industries, including healthcare, to enhance efficiency and reduce costs, with AI model performance improving steadily. In recent years, AI-based early detection of oral cancer using autofluorescence, photographic, and OCT imaging has emerged as a key research focus. Various AI-based imaging analyses were reviewed, confirming diagnostic values such as sensitivity and specificity. AI-assisted analysis of oral cancer showed a diagnostic sensitivity as high as 0.92, and while sensitivity for precancerous lesions was slightly lower, it still surpassed 90%. OCT shows particularly high sensitivity for precancerous lesions at 0.94.

Autofluorescence images are produced based on the property that collagen, elastin, and other endogenous fluorophores, such as nicotinamide adenine dinucleotide in mucosal tissues, emit autofluorescence under blue or ultraviolet light, with cancerous lesions displaying different fluorescence patterns. While autofluorescence imaging has been widely used in dentistry to screen for abnormal oral lesions, its accuracy has been reported as low, with sensitivity ranging from only 30% to 50%. This imaging technique has shown limited effectiveness in diagnosing oral cancer. Previous clinical studies primarily relied on differences in spectral fluorescence signals between normal and diseased tissues. Recently, however, time-resolved autofluorescence measurements, which utilize the varying fluorescence lifetimes of endogenous fluorophores, have been developed to address the issue of overlapping spectra, leading to improved image accuracy.

Advanced autofluorescence imaging, combined with AI algorithms, has reported diagnostic sensitivity for precancerous and cancerous lesions as high as 94%. AI-based diagnosis using autofluorescence images demonstrated an 85% sensitivity for all precancerous lesions. Although this is relatively lower compared to other imaging tools, autofluorescence imaging still holds value as a complementary diagnostic tool. Efforts are also underway to enhance diagnostic accuracy for oral cancer by integrating AI analysis of images from various tools alongside autofluorescence imaging.

Photographic imaging is a quick and convenient method with high accessibility compared to other adjunct techniques. However, its quality can vary significantly based on factors such as the camera, lighting, and resolution used during image capture. Unlike external skin lesions, the oral cavity is a complex three-dimensional structure, including the lips, teeth, and buccal mucosa, which can reduce the accuracy of the images. A recent study involving a smartphone-based device addressed this issue by using a probe for easier access to the oral cavity and enhancing image resolution. In today's world, where billions of people own smartphones, image diagnosis through these devices offers widespread accessibility. With AI, accurate and efficient screening of a large number of images is possible. AI-assisted diagnosis using photographic images has a diagnostic sensitivity exceeding 91% for detecting precancerous and cancerous lesions.

Optical Coherence Tomography (OCT) is a medical imaging technology that captures tissue images by analyzing the differences in physical properties between the reference light path and the light reflected from the tissue. OCT is non-invasive, using infrared light instead of X-rays, and provides the advantage of real-time image verification. Since its development in 1991, OCT has advanced to offer high-resolution images at faster speeds and has become an essential tool in the biomedical field. A study by Yang et al. reported that AI analysis of OCT images achieved a sensitivity and specificity of 98% or higher for diagnosing oral cancer. Thus, AI-driven OCT diagnosis holds significant value as a screening tool for oral lesions.

AI analysis of medical images can aid in making quick decisions regarding further diagnosis and treatment. The ability of AI to differentiate between precancerous lesions and normal tissue demonstrated high sensitivity, above 90%, supporting its potential as an effective screening method. While questions remain about AI's ability to fully replace human experts, AI-assisted oral cancer diagnosis has the potential to significantly reduce disease-related mortality and morbidity, particularly in low- and middle-income countries with limited healthcare resources. Developing large-scale image datasets to enhance the accuracy of AI analysis will be a critical step in advancing clinical applications.

There are certain limitations. First, the inclusion of data from various imaging tools introduced heterogeneity into the results. To address this, we evaluated the sensitivity of each imaging tool separately. Despite this, the study is significant as the first meta-analysis assessing the accuracy of AI-based image analysis. Second, even when the same imaging tool is used, variations in device quality and technique across different studies may impact diagnostic accuracy. Additionally, the images used to train AI algorithms may not fully capture the wide variety of oral lesions. Third, the lack of sufficient prospective studies comparing conventional examinations with AI-assisted imaging limits the interpretation of our results. Future research across diverse clinical settings will be essential to advance AI-assisted healthcare and ensure its success.[7]

7. Challenges

The development of machine learning (ML) models has faced several challenges. However, recent studies have made significant progress in ML applications, such as annotating two-dimensional landmarks and diagnosing oral diseases. Some of these technologies have achieved accuracy rates comparable to, or even exceeding, the current gold standard. In oral medicine, ML's capability to analyze images is especially valuable. Despite these advancements, many applications remain in the early stages and are not yet ready for clinical implementation. Overall, machine learning (ML) holds great potential for improving clinical efficiency and diagnostic accuracy. However, a key clinical challenge lies in the interpretability of ML models. For physicians to effectively communicate performance metrics and explain how the system reached its predictions, these models need to be both practical and user-friendly. Additionally, there are concerns among healthcare professionals about how these transformative tools might impact the dynamic between patients and clinicians.[8]

The integration of AI and ML technologies into routine dental practices for oral cancer screening is still in its early stages. Researchers have highlighted the potential of these technologies, particularly when combined with various imaging techniques. However, despite these advancements, the widespread adoption of AI in daily dental practice, specifically for oral cancer screening, remains limited. There is a lack of detailed data on the use of these technologies in dental practices, especially across different regions or countries. Further research is needed to explore potential geographical disparities in the adoption of AI and ML in dentistry.

Several technological challenges hinder progress, such as the need for sufficient data input, methodological rigor, and standards in AI development, as well as issues related to data curation, sharing, and readability. Additionally, the lack of transparency in the decision-making process and the need for specialized training to ensure effective implementation are key obstacles.

It is also crucial to establish guidelines and safeguards to protect patient privacy and uphold ethical standards, especially given the risks of privacy breaches with AI-driven methods. These challenges highlight the need for robust data protection measures in dental practices, including secure AI and ML technologies and stringent cybersecurity protocols. Despite the potential benefits of AI in improving care and efficiency, practical concerns—such as the value and utility of these solutions, financial costs, and ongoing ethical and privacy issues—continue to pose significant barriers to their widespread adoption.[9]

8. Future Considerations

The push for enhancing precision medicine, specifically improving individualised prognostication and management of oral cancer, is vital for better overall outcomes. However, it is important to note that the application of deep learning models in achieving precision medicine is still in its early stages. Several factors still require attention, as previously mentioned. For instance, standardization is needed in deep learning approaches, including improving data preprocessing, standardising the reporting of methodologies, and ensuring consistency in performance metrics of the models.

Additionally, these models must be externally validated with diverse cohorts to confirm that their reported accuracy is reliable. In fact, model accuracy should be based on external validation with independent cohorts to reflect true performance. To serve as an effective clinical support system, these models must outperform human experts. Therefore, significant efforts should be dedicated to developing robust AI algorithms capable of handling available clinical datasets while delivering acceptable prognostic performance. Furthermore, appropriate frameworks need to be established to guide the integration of these models into routine clinical practice. Failing to address these considerations may result in an accumulation of studies on the potential of deep learning for prognostication, without delivering tangible benefits to individual oral cancer patients.

It is crucial to resolve these issues before these models can be used in daily practice as a clinical support system, offering a second opinion to clinicians. Additionally, ongoing efforts are needed to increase the availability of multidimensional biological and clinical data for deep learning applications. Expanding the dataset volume is essential to fully realize the benefits of deep learning, which holds great promise as a tool for advancing precision medicine in oral cancer.[4]

9. Conclusion

Artificial intelligence is set to significantly reshape research on the early detection of oral cancer, leading to advancements in clinical practice overall. By enabling the automation of tasks through the identification of complex patterns, AI presents valuable opportunities. To fully realize these benefits, ongoing research is essential for the interdisciplinary integration of AI techniques. Progress in this area could pave the way for future studies and innovations.[10]

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None.

11. Conflict of Interest

None.

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