BULLETIN OF STOMATOLOGY AND MAXILLOFACIAL SURGERY
Volume 21, Issue 6

DOI: 10.58240/1829006X-2025.21.6-65

ORIGINAL RESEARCH

EARLY DETECTION OF ORAL CANCER USING CBCT WITH THE ASSISTANCE OF ARTIFICIAL INTELLIGENCE

Hussein Haleem Jasim *
* Assistant Professor, Department of Oral Diagnosis, College of Dentistry, University of Wasit
Corresponding author*: Assistant Professor, College of Dentistry, University of Wasit, Kut, Iraq*
halmhanawi@uowasit.edu.iq

Received: *May 5, 2025;* ***Accepted:*** *Jun. 23, 2025;* ***Published:*** *Jul. 6, 2025*

ABSTRACT

Oral cancer, seen across much of the world, continues to pose serious public health concerns. High rates of illness and death often stem from the discovery that comes late in the disease's course. Among malignancies of the mouth, "oral squamous cell carcinoma" holds the highest frequency, and better outcomes are tied closely to early diagnosis. Where detection comes sooner, responses to therapy often show more success, and the chance of survival rises. "Cone Beam Computed Tomography", a complex imaging system, provides layered three-dimensional views of the oral and facial regions. These images help bring subtle tissue changes to light.

Aim of the study: The study aimed to probe how reliably the combined AI-CBCT system could reflect the actual tissue conditions confirmed by histopathological findings.

Materials and Methods: A total of 400 individuals participated in the study. Age distribution extended from 18 to 60 years. Gender classification remained unsegregated and did not serve as a variable of analytical weight. From the overall group, 200 exhibited clinical indications suggestive of squamous cell carcinoma localized within the mandibular region and were placed in the experimental group. The other 200 did not show signs of the disease. Those were used as controls. CBCT images were captured to assist in identifying potential malignancies within the jaw structures. Initially, each image underwent examination by a skilled Radiologist; findings were noted in sequence, based on visual inspection and diagnostic experience. Following that, the identical images were processed through an AI-based system. The model, structured on a deep conventional neural framework, had been trained earlier using labeled CBCT scans. These included both normal and carcinoma-affected samples, allowing for pattern recognition across a range of anatomical presentations. The histopathological reports were obtained to confirm the cancerous cases (used as a reference for diagnostic certainty). Once all readings were compiled, from both manual and AI interpretations, comparative analysis was carried out. Statistical tests were used to explore the agreement between Radiologist assessments and AI outputs, in comparison to the histopathological results.

Results: Statistical analysis suggested that the contrast in cancer detection within the jaws, comparing AI output to Radiologist evaluations, did not reach the threshold for statistical significance at the 0.05 level (McNemar's Test = 2.77, p-value: 0.096). But AI performance still edged slightly ahead across all evaluated metrics, in particular, CBCT assessments aided by AI reached a higher specificity of 96.97% versus the Radiologist's specificity of 86.96% and better overall accuracy, 97.50% versus the Radiologist's accuracy of 92.00%, these differences, unlike the overall detection rate, did show statistical significance (Z-Score = -2.13, p = 0.034; Z-Score = -2.47, p = 0.014). Sensitivity came out nearly the same between the two. AI at 97.76%. Radiologists at 94.66%. The gap, while visible, didn't reach statistical significance. Z-score landed at 1.33. p-value read 0.185. Results lean slightly in favour of AI-supported assessments. Not a sweeping lead. Not across all metrics. Just a subtle tilt in performance.

Conclusion: The system based on artificial intelligence successfully identified early-stage cancers that are often difficult to detect through standard CBCT scans, where details can remain faint or uncertain. What emerges here is a direction that, while not without challenges, suggests real potential. Joining AI with CBCT points toward a shift, perhaps even a leap, in the broader landscape of oral cancer detection.

***Keywords*:** Oral cancer, Squamous cell carcinoma, Artificial Intelligence, CBCT, Computed-Beam Computed Tomography

INTRODUCTION

Oral malignancy remains a substantial burden within global public health frameworks, registering between 350,000 and 400,000 new diagnoses on an annual basis. Among oral neoplastic disorders, oral cancer (OC) demonstrates the highest occurrence, currently recognized as the sixth most widespread malignancy across populations worldwide [1]. Predominance appears stronger in males, especially those advancing through middle adulthood, while figures remain notably reduced in females [2]. Oral squamous cell carcinomas (OSCC), representing more than 90 percent of all oral cancers, consistently reflect this marked male inclination [3]. Across the past thirty years, despite movement in both diagnostic refinement and therapeutic innovation, the 5-year survival rate for oral squamous carcinoma has shown only minimal change. Meanwhile, documented growth in incidence and overall prevalence continues, with an evident rise in cases affecting younger cohorts as well [4,5]. The tongue emerges frequently, involved in roughly 20 to 40 percent of presentations; the floor of the mouth follows, 15 to 20 percent—together these two regions form a significant proportion of OSCC manifestations [6,7]. Other intraoral sites—gingivae, palate, the retromolar zone, buccal surfaces [8].

The ventral region of the tongue, along with the floor of the mouth, tends to be affected more frequently by squamous cell carcinoma. These regions are covered by thin, non-keratinised epithelium. That thinness allows deeper entry of carcinogens into the progenitor cell layer. Tobacco substances, alcohol in solution—such agents build up there over time, saturating the floor of the mouth and the underside of the tongue [4]. Cases involving the lip, hard palate, or upper gingiva show less inclination toward regional lymph node metastasis. They often progress slowly, with outcomes generally better than others. In contrast, malignancies of the tongue, lower gingiva, and mouth floor tend to behave with greater aggression. Spread to lymph nodes occurs more commonly there, with prognoses generally more guarded. Tumors arising toward the back of the oral cavity are, broadly speaking, more inclined to spread than similar ones at the front. Small, low-grade, well-differentiated variants usually invade nearby structures—connective tissues, muscle, or bone—before metastasis begins. The high-grade, poorly-differentiated types act differently; their progression is faster, their reach toward lymphatic regions is often early in disease development [9].

Oral squamous cell carcinoma (SCC) may emerge from a background of disorders often considered potentially malignant—oral leukoplakia, submucous fibrosis, erythroplakia, and dysplastic lesions of lichenoid character among them [10,11]. In the case of oral lichen planus, especially the erosive type, the literature remains divided. Some studies point to a link between this condition and SCC development. Others find no such correlation [4,11].

Oral cancer, or OC, presents a clear pattern in where and how often it occurs. Men tend to be affected more than women. Sharp rises in cases appear in places like South and Southeast Asia, parts of Europe, Latin America, and the Pacific. Tobacco and betel quid use, along with consistent alcohol consumption, are widely accepted as principal contributors to oral SCC risk. Recent work also draws attention to high-risk genotypes of human papillomavirus (HPV) and diets lacking in fresh produce as emerging components in the disease’s complex causative landscape [9,12]. Rates of oral SCC reach their peak across the Indian subcontinent, a region where chewing habits involving tobacco, betel quid, and areca-nut are especially entrenched [13]. The carcinogenic effects of these substances fluctuate with dosage, duration, frequency, and more so when combined, their harmful potentials compound and escalate [12].

From a histological perspective, oral cancer most often takes the form of squamous cell carcinoma. Known in clinical terms as oral SCC or OSCC, it originates in the squamous epithelium lining of the oral cavity or lip [2]. Regional spread into nearby lymphatic tissue occurs with notable frequency. OSCC tends to emerge in several high-incidence locations: the tongue, the lip, and, at times, within the salivary glands. It accounts for the overwhelming majority of diagnosed oral malignancies—around 90 percent. Prognosis grows more uncertain with the heightened risk of secondary primary tumors developing in the same general area. This pattern underscores the pressing need for precise diagnostics, alongside comprehensive, cross-disciplinary management approaches [14].

Early signs tend to be mild. Not always easy to notice. This often leads to delays in finding the disease. Such delays commonly let the disease advance to more severe stages, causing higher death and illness rates. Oral cancer continues as a major concern worldwide. Detecting it early remains essential for providing treatments that improve survival chances and outcomes [2]. Even with progress in medical technology, diagnosing OC still brings many challenges. Tests often involve invasive steps, and the information gathered requires careful and expert analysis. Traditionally, confirming OC depends on biopsy, followed by a detailed study of tissue samples [14].

Imaging methods come into play a role, magnetic resonance imaging and computed tomography, and positron emission tomography join the list. These techniques can catch things invisible to the naked eye, revealing hidden details. It can guide decisions. Still, often expensive. Not always present in smaller clinics. Some regions lack the tools. Some lack the staff. Access uneven. Cost limits use. Availability shapes care, not always available where needed most. These methods help, yet the financial burden they carry can be significant. Not always accessible. Not always practical. Often limited by resources. Results may shift depending on how the scan is performed. Microscopic examination of tissue remains the trusted approach for diagnosis. Still, the process takes time. Outcomes can differ, depending on who reads the slide [15]. Variations among pathologists add a layer of uncertainty. This subjectivity can affect accuracy. Such issues point to an urgent need for diagnostic methods that are both faster and more dependable in the field of oral oncology [16].

Recently, artificial intelligence has started to change the medical world in ways that weren't quite expected. New tools are coming up that may help catch oral cancer earlier, even before clear symptoms show. These tools can read and compare data, notice patterns, and give fast feedback that might help clinicians make decisions with more confidence and less delay [17]. Change is happening fast, especially when it comes to cancer care. Artificial Intelligence belongs to computer science, but it's not just about data storage. Instead, it's about building systems that learn, adapt, and make sense of information in ways that feel almost human. This ability shifts how many tasks get done, often in surprising ways. like solving problems, absorbing new information, and weighing choices based on what's known at the time [16]. The field doesn't rest on one method alone. It includes machine learning, deep learning, natural language processing, computer vision for reading images, and robotics. The range is broad. The pace is not slowing [17].

The employment of AI models in identifying, sorting, and anticipating oral cancer occurrences has become more prominent across medical research and practice [18]. Through analysis of complex visuals—histological slides, radiographs, intraoral imagery AI tools manage to interpret what often evades clinical expertise. Particularly, convolutional neural networks (CNNs), nested within the wider deep learning field, have reached considerable levels of accuracy, identified lesion irregularities and drawn lines between benign and malignant findings. These systems, fed with extensive datasets, detect nuanced visual signals rarely apparent to human assessment, thereby supporting more refined diagnostics and improved sensitivity metrics [19]. Artificial neural networks. Also called ANNs. Inspired by neurons in biology. Layer upon layer, data moves from one node. Then, another stepwise, slowly complex pattern emerges. CNNs (convolutional neural networks) are a kind of ANN. They do well with medical images. Radiographs, dental anomalies. That kind of thing. RNNs, recurrent neural networks, work differently. They handle sequences. Things that change over time. Like orthodontic treatment progress. Or temporomandibular joint disorder development [20].

Oral cancer with late diagnosis is a problem, automated systems could help. Systems with little human input, "Machine learning" boosts accuracy here. Deep learning, a subset, reduces human involvement. Especially with big data sets [21]. In dental practice, CBCT is quite often used as an imaging technique. It allows, with notable clarity and contrast, views of the bone, teeth, and air cavities within the oral region [22]. The arrival of CBCT changed dental imaging fundamentally, offering high-resolution, 3D views. These views help greatly, especially when planning treatments or making diagnoses in different dental specialties. Because it can detect diseases and show complex anatomical structures, it remains a key tool in modern dentistry.
Looking at how CBCT and artificial intelligence come together, recent studies reveal AI's potential to boost CBCT's diagnostic power. AI systems have performed as well as, or better than, human specialists in identifying various dental issues, such as caries, periodontal disease, and periapical lesions [23]. While keeping high accuracy, these AI-based methods can also slash the time needed for analyzing images [24]. Adding denoising modules to AI systems can improve both interpretability and diagnostic results. This effect is even more pronounced in areas where qualified clinicians are limited [25]. The combination of CBCT with AI does more than just simplify image reading on its own. It acts as an effective decision-support system. This synergy enhances diagnostic quality. Efficiency in dental diagnostics also sees improvement [23].

The current study aimed to monitor the reliability of the combined AI-CBCT system for cancer detection in the jaw.

MATERIALS AND METHODS

The study was carried out at the Department of Oral and Maxillofacial Radiology across several Specialized Dental Centers in Baghdad, Iraq, between October 2024 and May 2025. Four hundred patients took part. Ages ranged between 18 and 60 years, with no gender restrictions. Of these, 200 made up the experimental group; patients were suspected of squamous cell carcinoma of the jaws. The other 200 comprised the control group, showing no clinical signs or symptoms of oral cancer. Cone-beam computed tomography (CBCT) imaging was performed on all patients to get images with three-dimensional sections as part of their standard diagnostic routine.

At first, all CBCT images were analyzed by an experienced Radiologist (First Observer) and the readings were recorded. The second observer analyzed the same CBCT images using the AI model. The AI algorithm, based on deep conventional neural learning, was trained on a dataset of annotated CBCT scans, including both healthy and cancerous tissues. CBCT images were evaluated by the two methods independently, so that both observers were unaware of each other's results. Then, after the histopathological examination was conducted to confirm the diagnosis of cancer. All data obtained from the AI-assisted CBCT system and Radiologist observations were analyzed and compared with the data based on histopathological examination (as gold standard) using statistical tests to observe the reliability of the AI method.

The study made use of a deep learning approach to detect cancerous lesions in the jaws. Three-dimensional views were reconstructed from CBCT scans for this purpose. ResNet-50 architecture [26], a convolutional neural network with 50 layers, was employed. The network classified tissues into three groups: normal (Class I=0), precancerous (Class II=2), and cancerous (Class III=3). **Figure 1 and Table 1.**

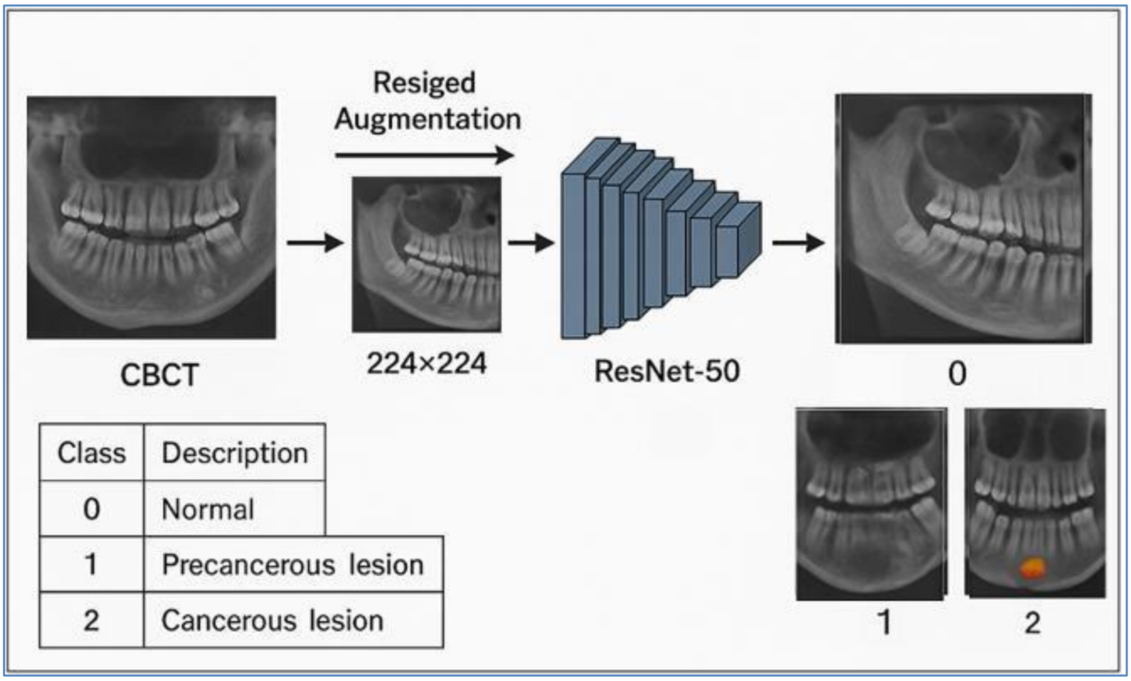

Figure 1. The diagram presents a deep learning pipeline built on ResNet-50. The goal: classifying jaw tissues in CBCT images. Categories include normal, precancerous, and cancerous. The pipeline covers multiple stages, starting with data preprocessing, followed by augmentation, then model training, and ending with classification output.

Table 1. Classification of tissues appearing in CBCT images applied in an AI model

Class	Tissue	ResNet50 Class
I	Normal tissue	0
II	Pre-cancerous	1
II	Cancerous tissue	2

Before training the model, one more step. The images were resized. All of them were adjusted to 224 by 224 pixels. This matched what ResNet 50 needed to process them. Pixel values were normalized afterwards, bringing them to a consistent range. To bring in more variation and hold back overfitting, several augmentation methods were used. Not just one approach. There were random flips, left to right. Small rotations added. Changes in contrast are applied.

The model used was ResNet 50. Not trained from the ground up. Started with weights from ImageNet. Then came the tuning, step by step, made to fit this task. The final layer, the one that makes predictions, was replaced. Now it gives three possible outputs. That matches the categories in the dataset. Training used a cross-entropy loss function. Optimization was carried out via stochastic gradient descent (SGD). The initial learning rate ranged between 1e-4 and 1e-3. Training lasted 50 epochs. Batch sizes varied, from 16 up to 32, depending on computational resources and dataset size.

A separate validation set was used to monitor performance and reduce overfitting. Model evaluation employed standard classification metrics: overall accuracy, class-wise area under the receiver operating characteristic curve (AUC), and confusion matrix analysis. The confusion matrix, in particular, was used to assess how well the model distinguished between normal, precancerous, and cancerous tissues.

Statistical analysis:

1- McNemar's Test assessed significant differences in the detection of cancer by a Radiologist and an AI model.

2- Two-Proportion Z-Test was used to compare the sensitivity, specificity, and accuracy of the AI model compared to Radiologist readings

3- Confidence intervals measured the reliability of sensitivity, specificity, and accuracy estimates.

RESULTS

The statistical analysis looked at cancer detection rates between AI and radiologists. The difference found was not strong enough to be statistically significant at a 5% threshold. McNemar's Test gave a value of 2.77 and a p-value of 0.096. Despite that, AI showed a small advantage across the various metrics examined. Specificity in AI-assisted CBCT analysis was higher, 96.97%, compared with 86.96% for Radiologists. Accuracy followed a similar pattern. AI scored 97.50%, radiologists came in at 92%. Both differences were statistically significant, with Z-Scores of -2.13 and -2.47. Corresponding p-values were 0.034 and 0.014. Sensitivity numbers came out close. AI reached 97.76 percent. Radiologists showed 94.66 percent. Not a large gap. The Z-score landed at minus 1.3. P-value at 0.185. Nothing in that range pointed to a strong difference.

Confidence intervals, set at 95 percent, give a clearer sense of how steady these values are. Sensitivity, specificity, and accuracy are each wrapped in their margins, not exact, but close enough to guide interpretation, showing the range where the true values for the population probably fall, assuming the process is repeated many times. For readings by Radiologists, sensitivity stands at 94.66%. The confidence interval stretches from about 89.4% up to 97.4%. Radiologists identify true cancer cases in a range, somewhere between 89% and 97%. The main estimate centers near 94.7%. Specificity for Radiologists is around 86.96%. The confidence interval spans roughly 77% to 93%. This suggests there is some variability when ruling out non-cancer cases. Accuracy comes in at 92%, confidence interval stretching from about 87% to 95%, showing solid overall diagnostic ability.
By contrast, AI-based CBCT detection shows higher precision and performance. Sensitivity reaches 97.76% with a narrower confidence interval from about 93.6% to 99.24%. Specificity also improves, hitting 96.97% to 97.76% interval between roughly 89.6% to 99.17%. Accuracy climbs to 97.50%, with confidence interval tighter, between about 94.28% to 98.93%. Though confidence intervals for sensitivity, for example, overlap between Radiologists and AI, which means no definitive statistical superiority without specific hypothesis tests, AI's higher point values and tighter intervals, especially in specificity and accuracy, suggest better consistency. This could mean fewer false negatives because sensitivity is better. At the same time, fewer false positives happen, thanks to improved specificity, when compared to Radiologist evaluations. That kind of precision, mixed with automated efficiency, makes AI a powerful aid. In some cases, it might even be the preferred option, especially where fast and dependable results are needed.
ROC analysis. AI showed a higher area under the curve, and the value was 0.974. Radiologists scored less, with an AUC around 0.908. This result points toward AI's better diagnostic performance. The basis for these findings: histopathological examinations. They serve as the gold standard. This enabled a comparison. Cancer detection reliability between AI-based CBCT images and Radiologist observations. Focused on oral cancer detection specifically. The findings suggest. AI can improve accuracy and precision. While keeping sensitivity at a high level. **Table 2, Figures 2, 3 and 4.**

Table 2. Confidence Intervals for sensitivity, specificity, and accuracy in Cancer detection. A comparison between radiologist readings and AI-based CBCT image analysis.

Metric	Radiologist readings (95% CI)	AI-based CBCT images (95% CI)
Sensitivity	89.38% – 97.39%	93.62% – 99.24%
Specificity	77.03% – 92.98%	89.61% – 99.17%
Accuracy	87.40% – 95.02%	94.28% – 98.93%

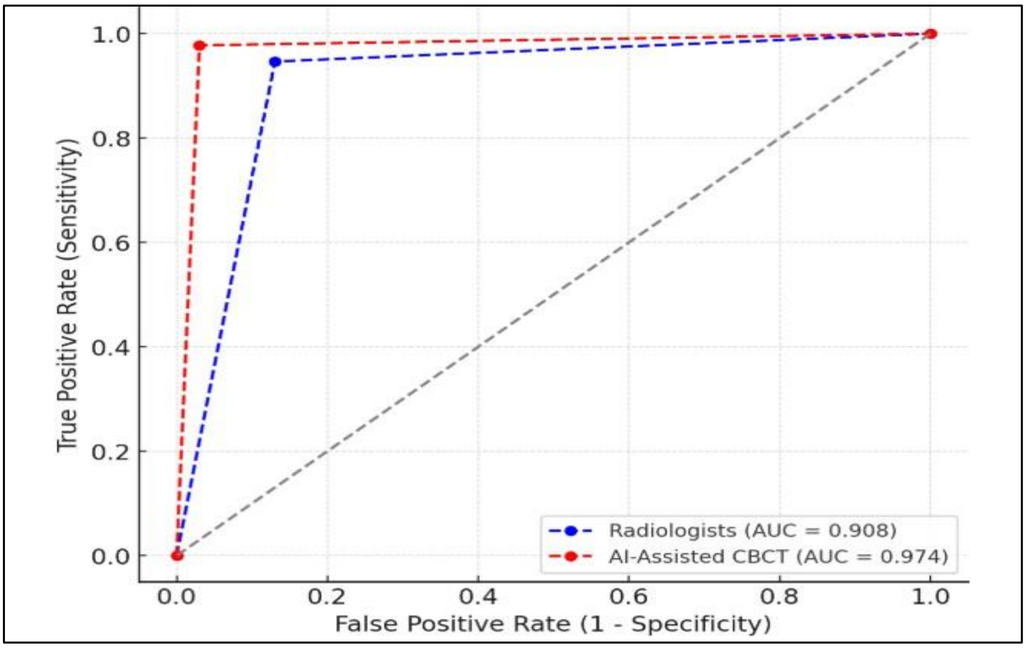

Figure 2. ROC Curve Analysis comparing AI-Assisted CBCT and Radiologist readings in cancer detection: AI-Assisted CBCT (Green Line): AUC = 0.974, Radiologists (Blue Line): AUC = 0.908

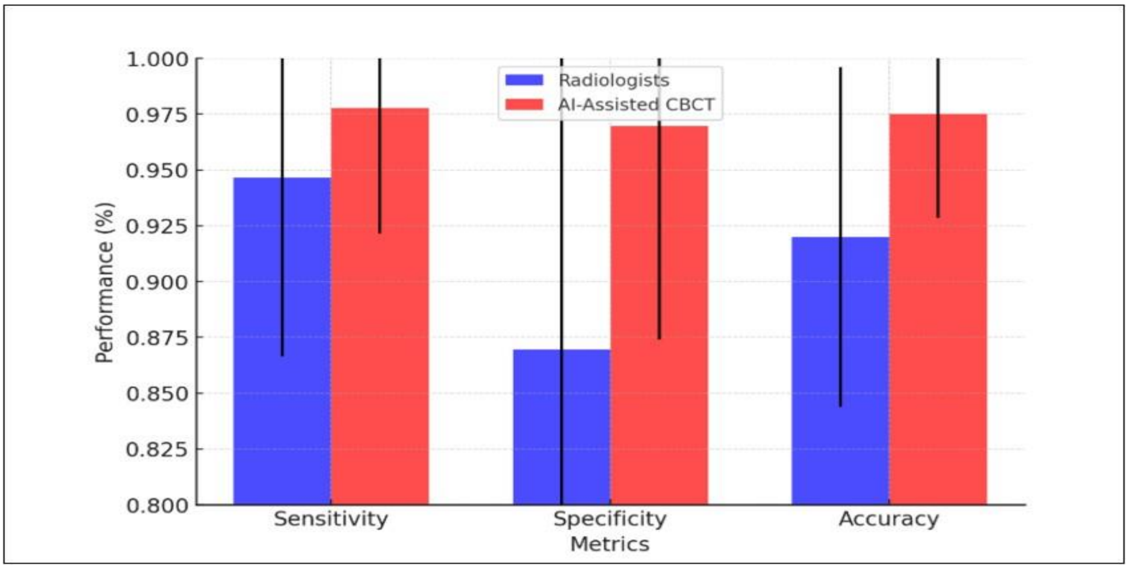

Figure 3. A bar chart presents sensitivity, specificity, and accuracy. It compares radiologists with AI-based CBCT images in cancer detection. Error bars display confidence intervals. AI, marked in red, shows clear superiority in specificity and accuracy. Sensitivity is slightly higher for AI. However, this difference lacks statistical significance.

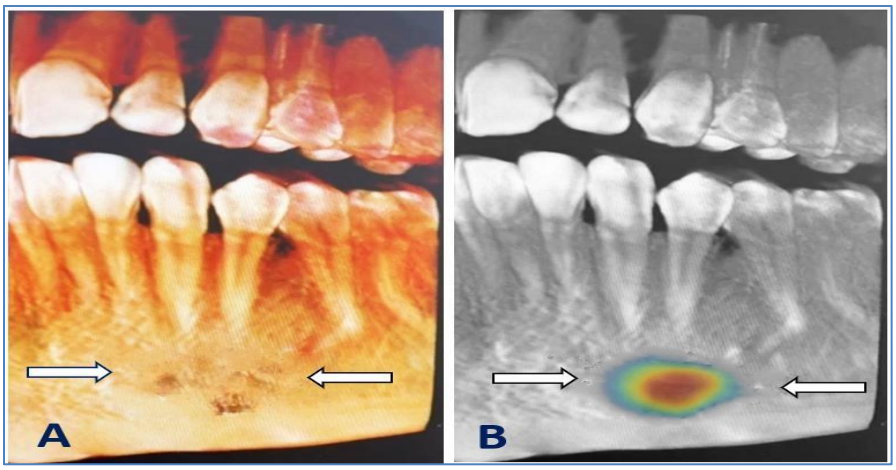

Figure 4. A three-dimensional CBCT image of a male patient (51-year-old) showed an early cancerous lesion in the mandible. **A:** A CBCT image without an AI model. **B:** A CBCT image aided by an AI model.

DISCUSSION

Artificial intelligence is rapidly transforming healthcare. It helps with diagnosing more accurate. Also, treatment planning becomes more efficient. Patient outcomes improve as well. Recent progress in AI, combined with molecular diagnostics, offers new tools. These tools hold promise for better diagnosis and more personalized treatment. Oral cancer diagnosis and prognosis face many challenges today. AI can ease some of these burdens. Workload drops, complexity lessens, and doctors experience less fatigue during diagnosis. This technology mimics human thinking. Because of that, it has drawn interest from scientists everywhere. Its use in dentistry is fairly new. But the early results seem quite promising.

One big challenge in oral cancer management. Many patients come with advanced disease. This contributes to high morbidity and mortality. Prognosis depends a lot on early detection. Accurate classification matters as well. Personalized treatment planning is key. Reducing human error plays a role. Cost-effectiveness is important too. AI has shown itself as a strong tool here [27]. It helps healthcare providers with clinical decision support systems. These systems provide guidance. The guidance draws from evidence. That alone can raise the level of diagnostic accuracy. Helps with treatment decisions as well.

In cancer research, Artificial Intelligence plays a growing role. Able to sift through massive stacks of biomedical texts. Can process layers of genomic data. From that, ideas start to form. Some lead to discovery. Some help rework how cancer gets found, and how it's treated [28].

Zhang et al. [29] developed deep learning models. They predict oral cancer using biopsy images. Also, CT scans played a role. Hyun et al., [30] worked with machine learning techniques. Methods such as random survival forests and deep neural networks. These performed better than traditional Cox models. Their focus was on oral squamous cell carcinoma prognosis. Risk stratification improved as a result. Yet, more validation studies are necessary. To confirm the clinical usefulness of these methods. Separately, Badawy et al., [31] proposed a method based on a conditional GAN. The goal was to reduce CBCT artifacts. This process created high-quality CT-like images. Improvements appeared in accuracy for radiotherapy planning and lesion assessment. This led to enhanced diagnostic and therapeutic precision.

Several researchers. Report that AI aids early detection of oral cancer. By identifying precancerous lesions. Such as leukoplakia and erythroplakia. These lesions have a higher risk. Of malignant transformation. AI tools also assess lesion progression risk. Helping with timely intervention. And ongoing monitoring [32].

Oral cancer, mainly oral squamous cell carcinoma, makes up most oral malignancies. Over ninety percent of cases. Despite progress in surgery, radiation, and chemotherapy. Five-year survival rates remain around fifty to sixty percent. This shows the need for early detection and new treatments [8,33,34]. Early diagnosis is crucial. Survival drops sharply with late-stage diagnosis. Traditional methods. Clinical exams and biopsies. Often fail to catch early lesions due to low sensitivity. Recently, cone-beam computed tomography has gained attention in oral health.

It provides high spatial resolution and 3D views. Also, the radiation dose is lower than with regular CT scans. When artificial intelligence is added to CBCT, especially systems trained with machine learning, new possibilities open up. AI can spot fine radiographic signs. Tiny shifts in structure. Often missed by the human eye. Catching these early can make a difference. It brings the chance to act sooner. And treat while the disease is still manageable.

The present study examined how well CBCT images, when supported by an AI model, can detect squamous cell carcinoma in the jaws. Results showed that AI-assisted CBCT analysis offered stronger diagnostic performance than Radiologist assessments. Although there were some differences in the way cases were misclassified, these did not reach statistical significance. The AI system showed high sensitivity and specificity, pointing to its strong potential in early cancer detection.In comparing both methods, Radiologist-based detection and AI analysis differences appeared in key diagnostic measures. Sensitivity was slightly higher for AI, about 97.76%, compared to 94.66%. for Radiologists. Still, the Z-test returned a p-value of 0.18. That result means the gap in sensitivity between AI and Radiologists did not reach statistical significance. Specificity, on the other hand, painted a clearer contrast. AI achieved 96.97%, Radiologist readings came in lower, at 86.96%. The difference here was more pronounced. A p-value of 0.034 confirmed that this gap held statistical weight. Accuracy leaned in favor of AI as well, 97.50% compared to 92% for Radiologist readings. The associated p-value, 0.014, confirmed that this difference was also statistically significant.

Although AI came out ahead in sensitivity, specificity, and overall accuracy, not every contrast met the threshold for statistical significance. Even so, the pattern of results points toward the AI-enhanced imaging being promising. Especially in early-stage cancer detection, this approach may offer greater reliability and diagnostic precision. The AI system performed better when analyzing CBCT scans. Its area under the curve came in at around 0.974. For Radiologists, that number was lower, closer to 0.908. This tells us that the AI was more effective at telling the difference between cancer and non-cancer cases. That kind of performance matters. A higher AUC means the system is more dependable. It's better at identifying who has the disease and who doesn't. In practice, this could mean fewer missed diagnoses and fewer false alarms.

AI also showed stronger results in other areas. It was more accurate overall and had a better track record of avoiding false positives. Sensitivity, or its ability to catch actual cancer, was slightly higher, but not by much. Statistically, the difference wasn't strong enough to stand out. The confidence intervals around the AI numbers were fairly tight. That tells us its results didn't bounce around much from one test to another. It's consistent. And that kind of stability can help when you're trying to make sense of difficult cases.

Baniulyte and colleagues found that AI systems used for detecting oral cancer had an average sensitivity of about 83%. Specificity was a bit higher, averaging around 87%. In simple terms, this means AI does a solid job spotting cancer, and an even better job recognizing when it's not there [35]. But the use of AI doesn't stop at diagnosis. It's also making strides in predicting outcomes. Machine learning tools now pull patterns from past clinical records, known risk factors, and a patient's health background to estimate the chances of cancer turning malignant [18,36,37]. Predictive models can identify people at higher risk even without symptoms. They use different factors. Age plays a role. Lifestyle habits matter. Overall health is part of the picture [38].

Even so, Radiologists still play a crucial role. Their expertise is important for those ambiguous or borderline cases. Sometimes, AI's pre-cancer labels overlap with unclear signs, which calls for human insight and judgment. Pairing Artificial Intelligence with CBCT imaging may push diagnostic accuracy further. Early signs of oral cancer, sometimes subtle, easily missed, could become more visible. The present work set out to explore how much CBCT can be trusted in spotting squamous cell carcinoma in the jaw. An AI model was used as a kind of aid, not the main focus, just part of the process.

CONCLUSION

AI proved quite good at spotting early-stage cancers, even when those cancers weren't very clear on standard CBCT images. It also processed scans faster, which lightens the load on radiologists and speeds up decision-making in clinical settings. Combining CBCT with AI looks like a promising way to catch oral cancer sooner. This approach brings better accuracy, faster results, and might help patients in the long run. Adding AI into everyday clinical routines could really boost what radiologists can do, catching oral cancers when treatments have the best chance.

As tech moves ahead, with stronger algorithms and bigger, varied training sets, the system should get even more accurate and dependable. AI's role is likely to grow in precise diagnostics and tailored treatment plans for oral cancer cases. There's also room for AI to team up with other tests, like tissue exams and blood markers, giving a fuller picture for diagnosis.

DECLARATIONS

Ethical approval

The study was conducted in accordance with the ethical standards of the Ethics Committee for Scientific Research at the College of Dentistry, University of Wasit, Ref. No. 172024 in 1/10/2024.

Informed consent Informed consent was obtained from all individual participants included in the study.

Funding The work was not funded.

Competing interest The author declares that there is no competing interest.

Acknowledgements Special thanks to all the specialized dental centers where the study was conducted.

REFERENCES

1-K. M. Fan, J. Rimal, P. Zhang, and N. W. Johnson, "Stark Differences in Cancer Epidemiological Data Between GLOBOCAN and GBD: Emphasis on Oral Cancer and Wider Implications," eClinicalMedicine 54 (2022): 101673.

2-M. García-Martín, P. Varela-Centelles, M. González, J. M. Seoane-Romero, J. Seoane, and M. J. García-Pola, "Epidemiology of Oral Cancer," Oral Cancer Detection: 81–93 .

3-Chamoli A., Gosavi A.S., Shirwadkar U.P., Wangdale K.V., Behera S.K., Kurrey N.K., Kalia K., Mandoli A. Overview of oral cavity squamous cell carcinoma: Risk factors, mechanisms, and diagnostics. Oral Oncol. 2021;121:105451. doi:

10.1016/j.oraloncology.2021.105451. [DOI] [PubMed] [Google Scholar][Ref list]

4-B. W. Neville and T. A. Day, "Oral Cancer and Precancerous Lesions," CA: A Cancer Journal for Clinicians, Vol. 52, No. 4, 2002, pp. 195-215. doi:10.3322/canjclin.52.4.195

5-A. D. Rapidis, P. Gullane, J. D. Langdon, J. L. Lefebvre, C. Scully and J. P. Shah, "Major Advances in the Knowledge and Understanding of the

Epidemiology, Aetiopathogenesis, Diagnosis, Management and Prognosis of Oral Cancer," Oral Oncology, Vol. 45, No. 4, 2009, pp. 299-300. doi:10.1016/j.oraloncology.2009.04.001

6-J. Bagan, G. Sarrion and Y. Jimenez, "Oral Cancer: Clinical Features," Oral Oncology, Vol. 46, No. 6, 2010, pp. 414-417. doi:10.1016/j.oraloncology.2010.03.009

7-I. O. Bello, Y. Soini and T. Salo, "Prognostic Evaluation of Oral Tongue Cancer: Means, Markers and Perspectives (I)," Oral Oncology, Vol. 46, No. 9, 2010, pp. 630-635. doi:10.1016/j.oraloncology.2010.06.006

8-S. Warnakulasuriya, "Global Epidemiology of Oral and Oropharyngeal Cancer," Oral Oncology, Vol. 45, No. 4, 2009, pp. 309-316. doi:10.1016/j.oraloncology.2008.06.002

9-J. P. Shah and Z. Gil, "Current Concepts in Management of Oral Cancer-Surgery," Oral Oncology, Vol. 45, No. 4, 2009, pp. 394-401. doi:10.1016/j.oraloncology.2008.05.017

10-C. Scully and J. Bagan, "Oral Squamous Cell Carcinoma Overview," Oral Oncology, Vol. 45, No. 4, 2009, pp. 301-308. doi:10.1016/j.oraloncology.2009.01.004

11-I. van der Waal, "Potentially Malignant Disorders of the Oral and Oropharyngeal Mucosa; terminology, Classification and Present Concepts of Management," Oral Oncology, Vol. 45, No. 4-5, 2009, pp. 317-323. doi:10.1016/j.oraloncology.2008.05.016

12-S. Petti, "Lifestyle Risk Factors for Oral Cancer," Oral Oncology, Vol. 45, No. 4, 2009, pp. 340-350. doi:10.1016/j.oraloncology.2008.05.018

13-E. Attar, S. Dey, A. Hablas, I. A. Seifeldin, M. Ramadan, L. S. Rozek and A. S. Soliman, "Head and Neck Cancer in a Developing Country: A Population-Based Perspective Across 8 Years," Oral Oncology,

Vol. 46, No. 8, 2010, pp. 591-596. doi:10.1016/j.oraloncology.2010.05.002

14-P. Polverini and M. Lingen, "A History of Innovations in the Diagnosis and Treatment of Oral and Head and Neck Cancer," Journal of Dental Research 98, no. 5 (2019): 489–497.

15-Z. Li, J. Hui, P. Yang, and H. Mao, "Microfluidic Organ-on-aChip System for Disease Modeling and Drug Development," Biosensors 12, no. 6 (2022): 370.

16-B. Ilhan, P. Guneri, and P. Wilder-Smith, "The Contribution of Artificial Intelligence to Reducing the Diagnostic Delay in Oral Cancer," Oral Oncology 116 (2021): 105254.

17-B. Khanagar, L. Alkadi, M. A. Alghilan, et al., "Application and Performance of Artificial Intelligence (AI) in Oral Cancer Diagnosis and Prediction Using Histopathological Images: A Systematic Review," Biomedicines 11, no. 6 (2023): 1612.

18- Ilhan B, Lin K, Guneri P, Wilder-Smith P. Improving oral cancer outcomes with imaging and artificial intelligence. J Dent Res. 2020;99(3):241-248. https://doi.org/10.1177/0022034520902128

19- Şahin GA. Advances in Articial Intelligence-aided Intraoral Imaging Analysis in Periodontics. BSJ Health Sci. 2024;7(5): 218-225. https://doi.org/10.19127/bshealthscience.1539717

20- Sohil F, Sohali MU, Shabbir J, James Gareth, Witten Daniela, Hastie Trevor, Tibshirani Robert. An introduction to statistical learning with applications in R: by. New York: Springer Science and Business Media; 2013. $41.98, eISBN: 978-1- 4614-7137-7, (2022).

21- Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.

22- Bernardes RA, de Moraes IG, Húngaro Duarte MA, Azevedo BC, de Azevedo JR, Bramante CM: Use of conebeam volumetric tomography in the diagnosis of root fractures. Oral Surg Oral Med Oral Pathol Oral Radiol Endod. 2009, 108:270-7. 10.1016/j.tripleo.2009.01.017

23- Ezhov M, Gusarev M, Golitsyna M, et al.: Clinically applicable artificial intelligence system for dental diagnosis with CBCT. Sci Rep. 2021, 11:15006. 10.1038/s41598-021-94093-9

24- Khabadze Z, Stolov L, Wehbe L, et al.: Implementation of ultra-short implants into dental practice: a systematic review. J Int Dent Med Res. 2023, 16:348.

25- Kim K, Lim CY, Shin J, Chung MJ, Jung YG: Enhanced artificial intelligence-based diagnosis using CBCT with internal denoising: clinical validation for discrimination of fungal ball, sinusitis, and normal cases in the maxillary sinus. Comput Methods Programs Biomed. 2023, 240:107708. 10.1016/j.cmpb.2023.107708

26- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 770-778).

27- Van Staveren HJ, Van Veen RLP, Speelman OC, Witjes MJH, Star WM, Roodenburg JLN. Classification of clinical autofluorescence spectra of oral leukoplakia using an artificial neural network: a pilot study. Oral Oncol. 2000;36: 286–93.

28-D. B. Flora, "Introducing AI in Precision Oncology," AI in Precision Oncology 1, no. 1 (2024).

29-G. Kim, "History in the AI Age, Computational History," SARIM 76 (2021): 1–29.

30-C. M. Hyun, T. Bayaraa, H. S. Yun, T. Jang, H. S. Park, and J. K. Seo, "Deep Learning Method for Reducing Metal Artifacts in Dental Cone-Beam CT Using Supplementary Information From Intra-Oral Scan," Physics in Medicine & Biology 67, no. 17 (2022): 175007.

31-M. Badawy, H. M. Balaha, A. S. Maklad, A. M. Almars, and M. A. Elhosseini, "Revolutionizing Oral Cancer Detection: An Approach Using Aquila and Gorilla Algorithms Optimized Transfer Learning-Based CNNs," Biomimetics 8, no. 6 (2023): 499.

32- Mira ES, Saaduddin Sapri AM, Aljehanı RF, Jambı BS, Bashir T, El-Kenawy ES, Saber M. Early diagnosis of oral cancer using image processing and Artificial intelligence. Fusion: Pract Appl. 2024;14(1).293-308. https://doi.org/10.54216/FPA.140122

33- Siegel RL, et al. Cancer statistics, 2023. *CA Cancer J Clin.* 2023;73(1):17-48. doi:10.3322/caac.21763

34- Lingen MW, et al. Critical evaluation of diagnostic aids for the detection of oral cancer. *Oral Oncol.* 2008;44(1):10-22. doi:10.1016/j.oraloncology.2007.06.011

35- Baniulyte G, Ali K. Artificial intelligence – can it be used to outsmart oral cancer? Evid. Based. Dent. 2022;23:12–3. https://doi.org/10.1038/s41432-022-0238-y.

36- Alhazmi A, Alhazmi Y, Makrami A, Masmali A, Salawi N, Masmali K, Patil S. Application of artificial intelligence and machine learning for prediction of oral cancer risk. J. Oral Pathol. Med. 2021;50:444–50. https://doi.org/10.1111/jop.13157.

37- Hung M, Park J, Hon ES, Bounsanga J, Moazzami S, Ruiz-Negro´n B, Wang D. Artificial intelligence in dentistry: harnessing big data to predict oral cancer survival. World J. Clin. Oncol. 2020;11:918–34. https://doi.org/10.5306/wjco.v11.i11.918.

38- Kar A, Wreesmann VB, Shwetha V, Thakur S, Rao VUS, Arakeri G, Brennan PA. Improvement of oral cancer screening quality and reach: the promise of artificial intelligence. J. Oral Pathol. Med. 2020;49:727–30. https://doi.org/10.1111/jop.13013.