Validation of the Efficacy of Artificial Intelligence in Detecting the Common Dental Diseases Prevailing in Patients

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KEYWORDS

Artificial Intelligence, Dentistry, Intraoral-images, Orthopantomograms, dental findings, diagnosis, treatment plan

ABSTRACT

Aim: To access the efficiency, reliability and accuracy of detecting dental ailments by Artificial intelligence(AI) machines**Material and Methods**: In this study, 454 volunteers provided informed consent, resulting in 227 Orthopantomograms (OPGs) and 681 intraoral images. An AI kiosk captured images of their anterior teeth, upper arch, and lower arch to assess dental parameters such as caries, edentulous spaces, malocclusions, root stumps, bone loss, furcation defects, impactions, nerve and sinus involvement, spacing and crowding, The AI's identification of dental issues was validated by a dentist for accuracy, and the collected data was analysed to evaluate its significance. The area under the receiver operating characteristic (ROC) curve allowed a comparison of efficacy between network and examiner diagnosis.**Results:** Crosstab statistics were computed to determine the test's sensitivity and specificity. Various aspects and variables were recorded and are presented in the following tables. The positive predictive value (PPV) and negative predictive value (NPV) were calculated to assess the accuracy of the AI method for identifying dental findings. IBM SPSS version 25 was used for these calculations.**Conclusion:** The machine learning algorithms developed in this study exhibit strong performance and enable effective implementation by dental and non-dental professionals. Clinicians are encouraged to utilize the algorithms from this study for early intervention and treatment strategies.

1 | INTRODUCTION:

Dentistry has seen significant advancements in recent years, with AI playing a key role in many of these changes. AI integration promises to revolutionise diagnostics, treatment, and patient outcomes by streamlining processes and improving precision**. [1]** AI applications in dentistry include image analysis, predictive models, decision support systems, and robotic automation. These technologies enhance practitioners' performance by enabling early disease detection and prevention through pattern recognition and image analysis algorithms. This, in turn, improves the efficiency of radiographic interpretation, speeds up diagnoses, and allows for early treatment of oral diseases. [2]

In Krois et al.'s study, one limitation was the cross-validation approach, which lacked a fully independent hold-out test set, potentially introducing a slight performance bias. To address this, our study implemented triple blinding, which enhanced objectivity and minimized potential biases. [3] This study aims to check the reliability of an AI tool developed to detect basic dental diseases using Orthopantomograms (OPGs) and intraoral images, with a focus on demonstrating its accuracy as a valuable complement to professional dental judgment. Successful validation of AI in identifying common oral diseases will support its integration into standard clinical workflows, benefiting both patient care and healthcare professionals.

2 | MATERIALS AND METHODS

The study proposal was approved by the Institutional Human Ethics Committee, which issued the approval number 360/IRB-IBSEC/SIST, dated 16th April 2024.

A total of 227 OPGs and 681 intraoral images were obtained from 454 volunteers who provided informed consent for participation in this study. These participants were screened using an AI kiosk, which captured intraoral images encompassing the anterior teeth, upper arch, and lower arch to evaluate various dental parameters, including dental caries, edentulous spaces, skeletal and dental malocclusions, root stumps, bone loss, furcation defects, impactions, nerve and sinus involvement, crossbite, open bite, underbite, deep bite, overjet, spacing, crowding, and proclination. The AI's identification of dental issues was verified for accuracy by a dentist, and the collected data underwent analysis to assess its significance.

2.1 | Participant Recruitment

A total of 454 volunteers were recruited for this study following the provision of informed consent. Detailed information regarding the study objectives, procedures, potential risks, and benefits was provided to all participants. Written informed consent was obtained from each volunteer before any data collection. The participants were evaluated using AI kiosk as well as Ai dent web application for intraoral imaging and OPGs.

2.2 | Imaging and Data Collection

We built an in-house dataset consisting of 227 OPGs and 681 intraoral images to evaluate the deep learning model. All the data were acquired at the Department of Oral Medicine and Radiology, Sathyabama Dental College, Chennai between May 2024 and July 2024. These imaging techniques were employed to ensure a thorough examination of dental and skeletal structures.

2.2A | AI Kiosk Imaging:

Procedure: Each participant underwent intraoral imaging using an AI-powered kiosk. The AI kiosk was designed to capture high-resolution detailed intraoral images, including Anterior teeth, Upper arch, and Lower arch. These images were utilized to evaluate a comprehensive set of dental parameters: Stains, Calculus, Missing, Crowns, Filling, Pericoronitis, Root stumps, Deep caries, grossly decayed, Pit and fissure caries, Fracture, Spacing, Diastema, Malocclusions, Attrition, Gingivitis.

AI Analysis: The AI system processed the images to identify the presence of these dental issues. The results were stored in a secure database for further analysis.

2.2b | AI Web Application Imaging:
Ai Dent is a cloud-based software service that provides automated dental X-ray analysis in real-time using AI (Deep Learning) technology in combination with deep dental domain knowledge.
Procedure: Each participant provided an OPG (Orthopantomogram) image, which was uploaded to an AI-powered web application. The AI application analysed the OPGs to evaluate various dental parameters, including Dental caries, Calculus, Fracture, Root stumps, Bone loss, Furcation defects, Impactions, Fillings, Root canal-treated teeth (RCT), Abscesses, Attrition, Crowns, Implants, Braces, Nerve involvement, Sinus involvement.
AI Analysis: The AI system processed the OPG images to identify these dental issues. The results were securely stored for subsequent analysis.

2.3 | Verification by a Dentist
A licensed dentist, blinded to the AI findings, independently reviewed the intraoral images and OPGs. The dentist's evaluation served as the gold standard for verifying the AI's accuracy in identifying dental issues. Discrepancies between the AI and dentist evaluations were noted and documented.

2.4 | Statistical Analysis
The crosstab statistics were computed to formulate the sensitivity and specificity for the test. Different aspects were counted for, different variables were recorded and represented in the following tables. The positive predictive value (PPV) and Negative predictive value (NPV) was calculated to show the accuracy of the AI method of determination of oral lesions. IBM SPSS statistical software version 25 was used to calculate the same.
The area under the curve (AUC): The AUC is broadly utilized to degree the precision of demonstrative tests. The closer the ROC bend is to the upper left corner of the graph, the higher the rate of accuracy of the test. It is because in the upper left corner, the sensitivity = 1 and the false positive rate = 0 (specificity = 1). In common, an AUC of 0.5 determines no discrimination (i.e., ability to diagnose the patients with and without the finding or condition based on the test), 0.7 to 0.8 is considered satisfactory, 0.8 to 0.9 is considered excellent, and more than 0.9 is considered exceptional. [4]

2.5 | Ethical Considerations
This study was conducted in compliance with ethical guidelines, ensuring that all participants provided informed consent and their data was handled with confidentiality and integrity.

3 | RESULT ANALYSIS
The crosstab statistics were computed to formulate the sensitivity and specificity for the test. Sensitivity measures how well the test detects true positives (correctly identifying those with the condition). High sensitivity means fewer false negatives. Specificity measures how well the test detects true negatives (correctly identifying those without the condition). High specificity means fewer false positives. Different aspects were counted for, different variables were recorded and represented in the following **Table 1, Table 2, Table 3**. The positive predictive value (PPV) and Negative predictive value (NPV) were calculated to show the accuracy of the AI method of determination of oral lesions. Positive Predictive Value (PPV) is the proportion of positive test results that are true positives. High PPV means that if the test result is positive, there’s a high probability the condition is actually present. Negative Predictive Value(NPV) is the proportion of negative test results that are true negatives. High

NPV means that if the test result is negative, there's a high probability the condition is not present. IBM SPSS statistical software version 25 was used to calculate the same.

The area under the curve (AUC) is broadly utilized to degree the precision of demonstrative tests. The blue line is the ROC curve which represents the performance of the classification model across different thresholds. The red line is the diagonal which represents the performance of a random classifier, which makes random guesses. The closer the ROC bend is to the upper left corner of the graph, the higher the rate of accuracy of the test. It is because in the upper left corner, the sensitivity = 1 and the false positive rate = 0 (specificity = 1). In common, an AUC of 0.5 determines no discrimination (i.e., ability to diagnose the patients with and without the finding or condition based on the test), 0.7 to 0.8 is considered satisfactory, 0.8 to 0.9 is considered excellent, and more than 0.9 is considered exceptional.

	Caries	**Calculus**	**Fracture**	**Furcation Involvement**	**Bone Loss**	**Root stump**
Sensitivity	99	100	100	100	98.4	98.7
Specificity	68	100	100	33.33	52.0	91
PPV	0.68	1	1	1	0.97	0.98
NPV	0.75	1	1	0.59	0.67	0.91
AUC	0.835	0.500	0.500	0.667	0.752	0.949
P Value		1.00	1.00	0.090	<0.0001*	<0.0001*

*statistically significant

TABLE 1: Performance Metrics for the dental parameters including dental caries, calculus, fracture, furcation involvement, bone loss and root stump

	Impacted teeth	**Unerupted teeth**	**Filled teeth**	**RCT**	**Abscess**	**Attrition**
Sensitivity	100	99.5	97.9	99.4	99.4	98.5
Specificity	69.2	93.8	87.5	94.4	48.9	84.6
PPV	1	0.99	0.97	0.94	0.66	0.86
NPV	0.76	0.94	0.88	0.99	0.98	0.98
AUC	0.846	0.966	0.927	0.96	0.742	0.916
P Value	<0.0001*	<0.0001*	<0.0001*	<0.0001*	<0.0001*	<0.0001*

*statistically significant

TABLE 2: Performance Metrics for the dental parameters including Impacted teeth, Unerupted teeth, filled teeth, RCT, Abscess, Attrition

	Crowns	Implant	Braces	Nerve Involvement	Sinus involvement
Sensitivity	98.2	100	98.7	100	100
Specificity	98.2	100	100	100	100
PPV	0.98	1	1	1	1
NPV	0.98	1	0.98	1	1
AUC	0.982	1.00	0.993	-	-
P Value	<0.0001*	0.003*	<0.0001*	-	-

*statistically significant

TABLE 3: Performance Metrics for the dental parameters including Crowns, Implant, Braces, Sinus and Nerve Involvement

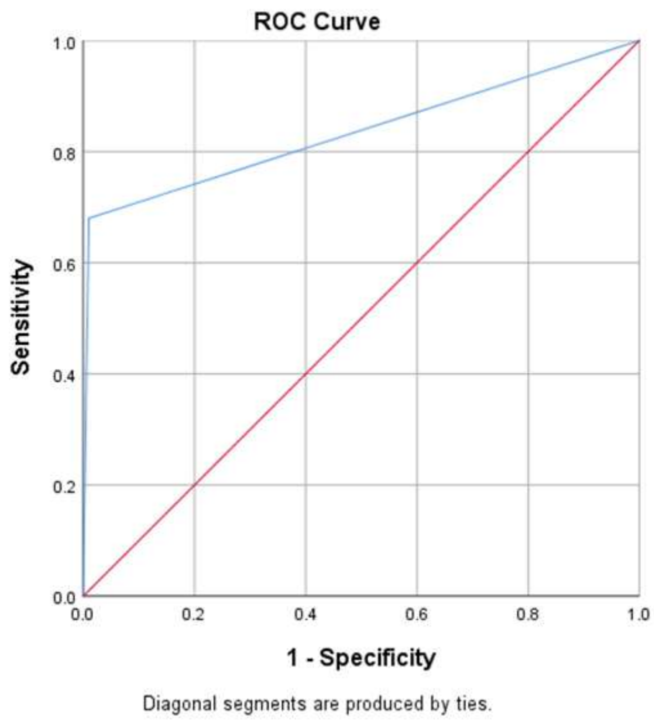

Figure 1: **ROC for comparison of the Caries.** It shows High sensitivity (99) but relatively low specificity (68), meaning it detects most caries cases but has a moderate rate of false positives. AUC of 0.835 shows good overall test performance.

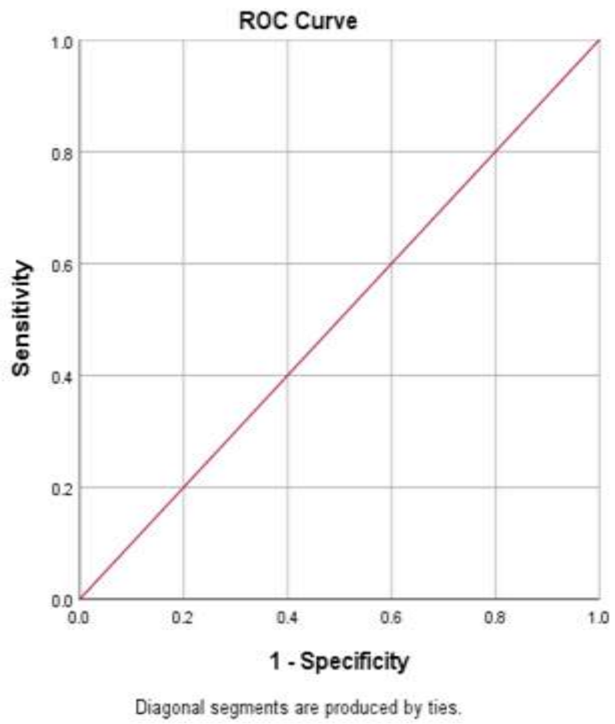

Figure 2: **ROC for comparison of the Calculus and Fracture.** It shows perfect sensitivity and specificity (100 for both), suggesting the test is ideal at detecting calculus with no false negatives or positives. AUC of 0.5 indicates random test performance, which could suggest that despite the perfect metrics, there might be issues in the test's real-world application, there might be possible practical limitations.

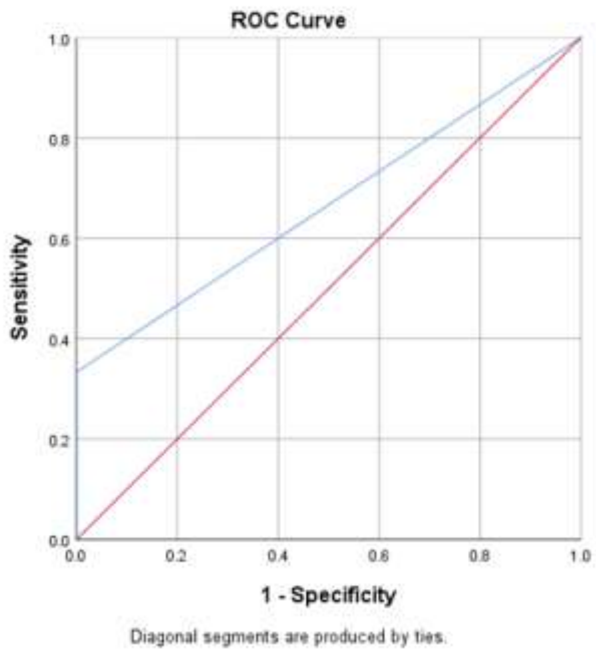

Figure 3: ROC for comparison of the Furcation involvement. It shows that the sensitivity is high (100), but specificity is relatively low (33.33), meaning the test is good at detecting furcation involvement but may produce many false positives. AUC of 0.667 suggests moderate discriminatory power.

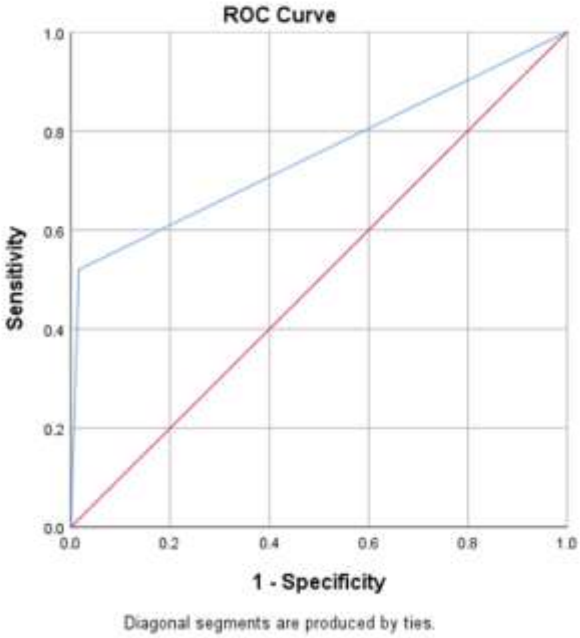

Figure 4: ROC for comparison of the Bone Loss. Good sensitivity (98.4) and moderate specificity (52.0). High AUC (0.752) and significant P-value (<0.0001) indicate good test performance with significant results.

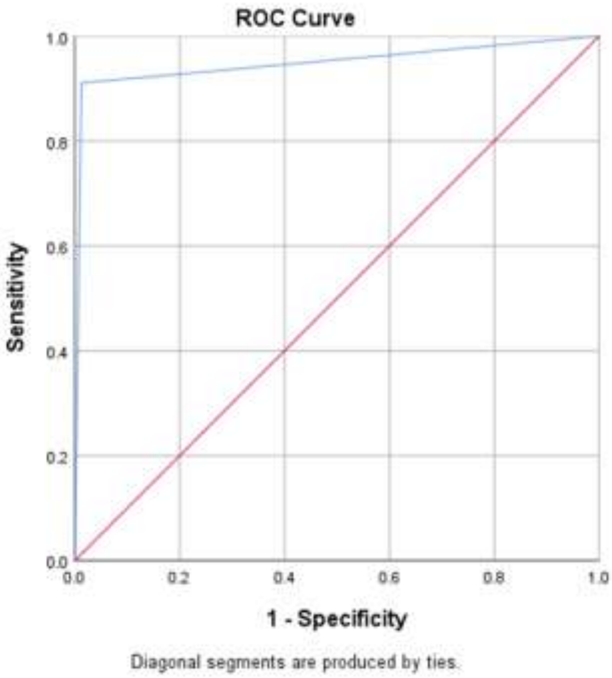

Figure 5: ROC for comparison of the Root Stump lesion. High sensitivity (98.7) and specificity (91), meaning the test works well for root stump detection. AUC of 0.949 and a highly significant P-value (<0.0001) indicate excellent test performance.

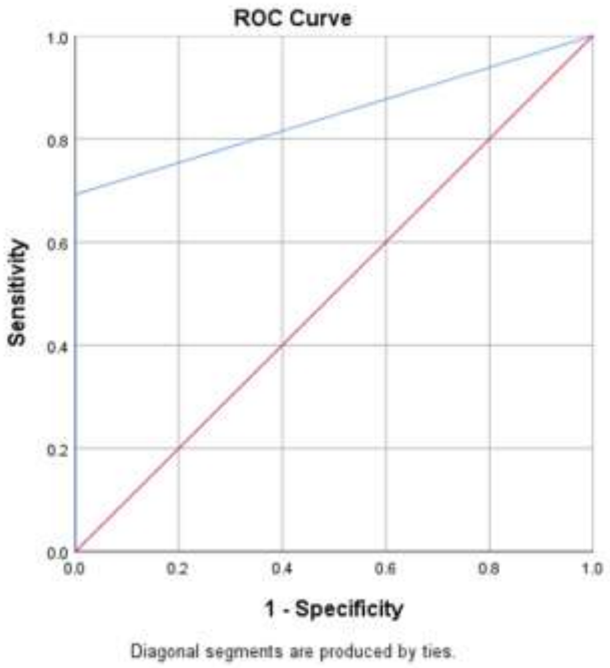

Figure 6: ROC for comparison of the Impacted teeth: It shows high sensitivity (100%) and moderate specificity (69.2%), with an AUC of 0.846, indicating good overall diagnostic performance.

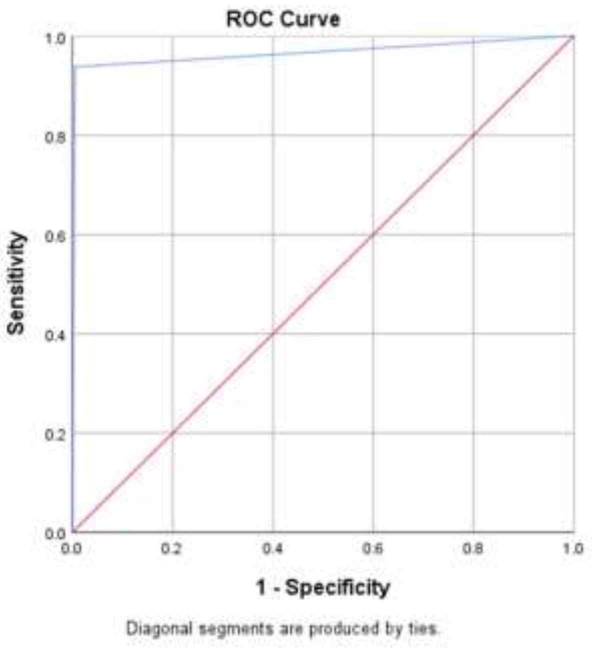

Figure 7: ROC for comparison of the Un-erupted teeth: It shows high sensitivity (99.5%) and specificity (93.8%), with a very high AUC (0.966), making it a reliable test.

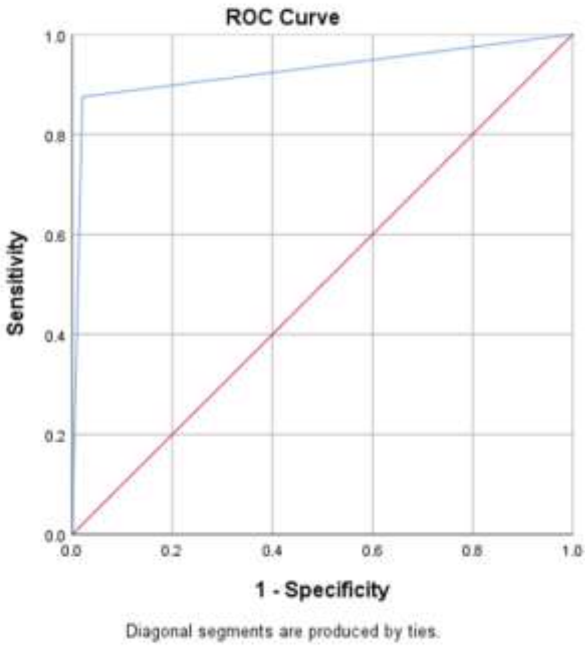

Figure 8: ROC for comparison of the Filled lesion: It shows sensitivity of 97.9% and specificity of 87.5%, with an AUC of 0.927, indicating strong diagnostic capability.

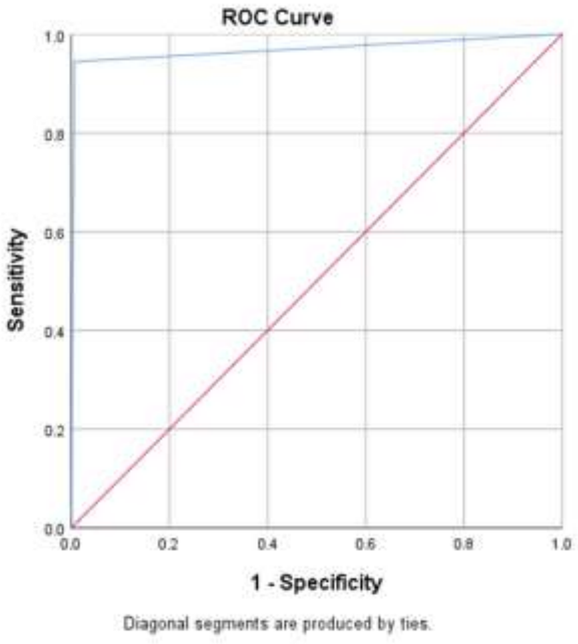

Figure 9: ROC for comparison of the Root canal treated teeth: High sensitivity (99.4%) and specificity (94.4%), with an AUC of 0.96, showing excellent performance.

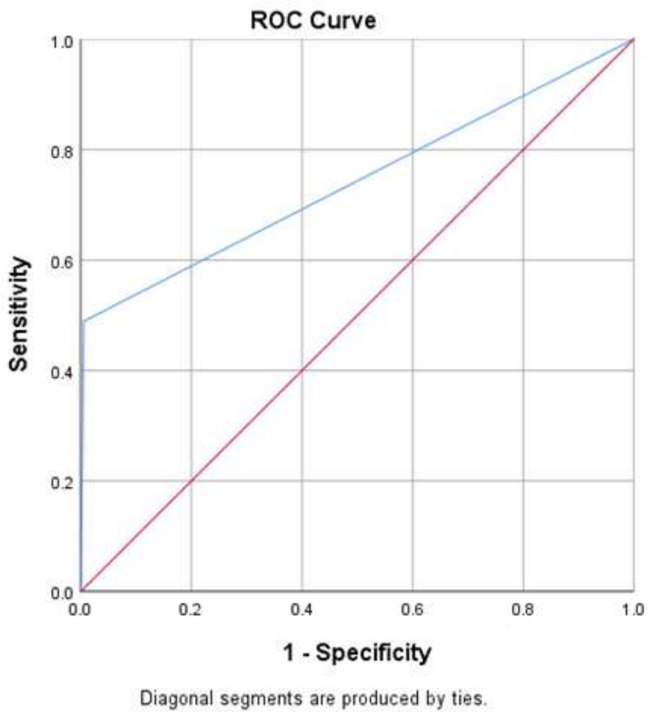

Figure 10: ROC for comparison of the Abscess: High sensitivity (99.4%) but lower specificity (48.9%), with an AUC of 0.742, meaning it detects most cases but with a higher rate of false positives.

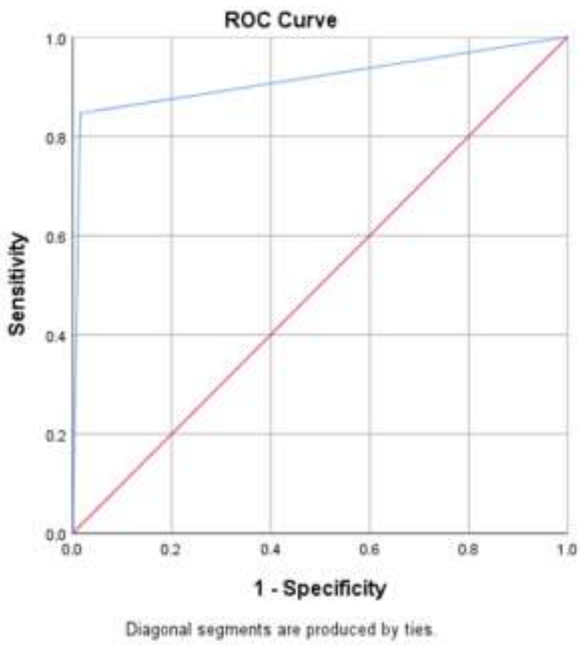

Figure 11: ROC for comparison of the Attrition: Good sensitivity (98.5%) and specificity (84.6%), with an AUC of 0.916, indicating reliable diagnostic performance.

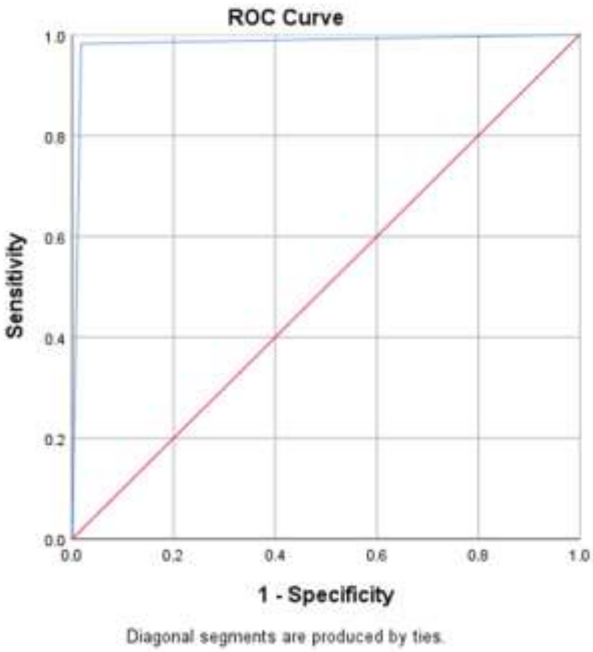

Figure 12: ROC for comparison of the Crowns: High sensitivity (98.2%) and specificity (98.2%), with a strong AUC (0.982), indicating very good diagnostic performance. The P-value (<0.0001) confirms statistical significance.

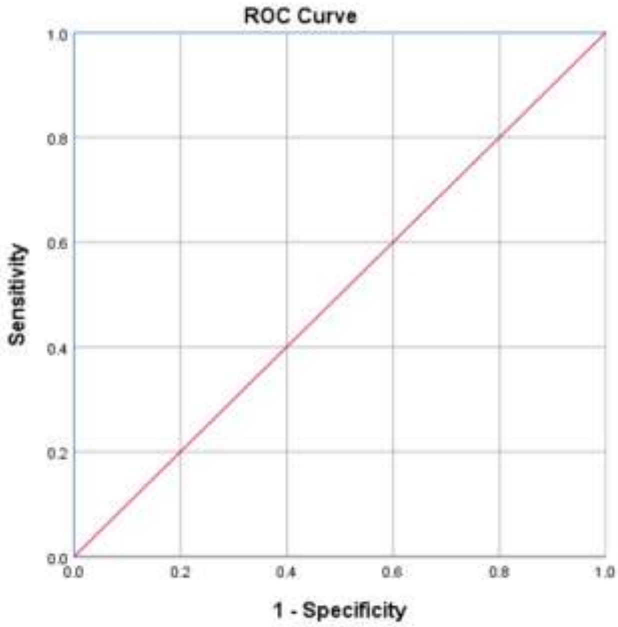

Figure 13: ROC for comparison of the Implants: Perfect sensitivity (100%) and specificity (100%) with an AUC of 1.0, suggesting flawless diagnostic performance. The P-value (0.003) is statistically significant.

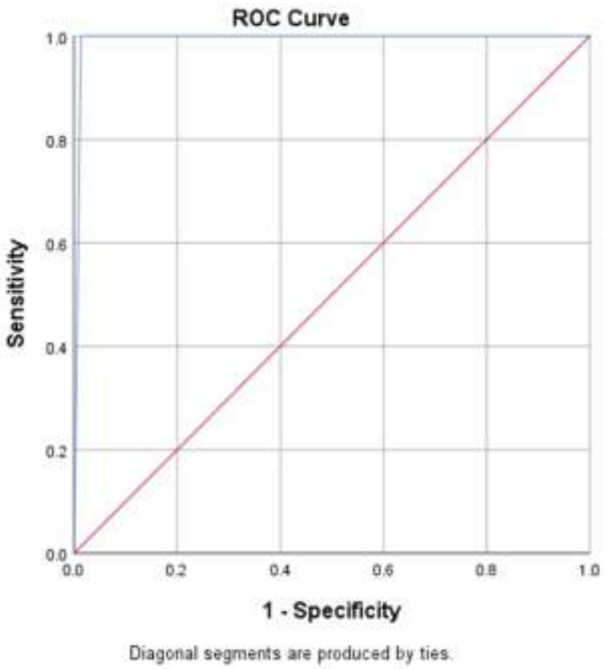

Figure 14: ROC for comparison of the Braces, Nerve involvement, Sinus involvement: High sensitivity (98.7%) and specificity (100%) with an AUC of 0.993, indicating excellent diagnostic performance. The P-value (<0.0001) shows statistical significance.

The metrics show that Caries and Bone Loss have good discriminatory power based on their AUC values which can be appreciated in **Fig. 1 and Fig. 4**, while Root Stump detection observed in **Fig. 5** is highly reliable with strong sensitivity, specificity, and AUC. In **Fig. 2**. Calculus and Fracture display perfect sensitivity and specificity, though caution is needed with their AUC. **Fig. 3** shows that furcation Involvement could improve due to low specificity. Unerupted Teeth, Filled Teeth, and RCT observed in **Fig. 7, 8, 9** show the highest diagnostic reliability. Fig. 10 shows that abscess has moderate AUC and low specificity, indicating potential false positives. **Fig. 12, 3, 14** shows that Implant, Braces, and Crowns are highly reliable, while Nerve Involvement and Sinus Involvement show perfect metrics, though lacking AUC and P-values, suggesting the need for further validation. All tests have statistically significant P-values (<0.0001).

4 | DISCUSSION:

The integration of AI in dentistry has transformed the field, equipping dentists with advanced tools to improve diagnosis and patient care. AI-driven algorithms can process vast amounts of data, such as radiographs, images, and patient records, to detect patterns and make precise predictions with impressive speed and accuracy. [5]

Since smartphones with powerful cameras are becoming ubiquitous, multiple studies have also discussed the possibility of tele dentistry based on oral photographs from smartphones. Estai M et al evaluated the efficacy of detecting dental caries from smartphone photographs, where the sensitivity scores of dentists ranged from 609 to 639%6, which is lower than the benchmark visual examination (Estai et al, 2017), However, only labial and occlusal views of teeth were captured in the study, which was reported to cause the missing of dental caries detections. [6]

Kohara et al further studied the performance of dentists' detection of different stages of caries lesions from smartphone photographs (Kohara et al 2018) Their results show that sound teeth and extensive lesions can be detected with high sensitivity from 75% to 100%, while the initial and moderate lesions have a detection sensitivity lower than 60%. Moreover, the detection specificities for lesions of all stages were always above 83.3%. [7]

Krois et al. evaluated a convolutional neural networks (CNN) model's ability to detect periodontal bone loss in panoramic X-rays (OPGs), but their study faced some limitations. Primarily, the analysis focused on manually cropped sections of the images rather than the entire dentition, which could potentially reduce diagnostic accuracy. Since oral conditions often appear in clusters, analyzing the whole dentition might provide more comprehensive insights. Additionally, they performed cross-validation without using a completely independent test set, which could introduce data leakage, possibly affecting the model's generalization and resulting in a slight bias in performance estimates. [8]

AI has revolutionized how dental professionals can interpret OPGs and intraoral images, significantly enhancing diagnostic accuracy. By leveraging deep learning models such as CNNs, AI systems can analyse complex dental structures, including teeth, roots, and surrounding bone, with a high degree of precision. These systems are trained on large datasets of OPGs and intraoral images, allowing them to detect a range of dental conditions and findings like caries, impacted teeth, Fracture, Root stumps, Bone loss, Furcation defects, Impactions, Fillings, Root canal-treated teeth, Abscess, Attrition, Crowns, Implants, Braces, Nerve involvement, Sinus involvement. [9]

A dentist independently reviewed these images to verify AI accuracy, and statistical analyses, including sensitivity, specificity, PPV, NPV, and AUC, were conducted. The study's findings indicate the AI's promising accuracy in identifying various dental conditions, with high sensitivity and specificity, and excellent AUC values for most parameters. Ethical guidelines ensured participants' informed consent, and IBM SPSS software aided data analysis. The ROC curve was used to visualise the AI model's diagnostic performance, with AUC values indicating exceptional to satisfactory accuracy across conditions. The metrics show that Caries and Bone Loss have good discriminatory power based on their AUC values, while Root Stump detection is highly reliable with strong sensitivity, specificity, and AUC. Calculus and Fracture display perfect sensitivity and specificity, though caution is needed with their AUC. Furcation Involvement could improve due to low specificity. Unerupted Teeth, Filled Teeth, and RCT show the highest diagnostic reliability. Abscess has moderate AUC and low specificity, indicating potential false positives. Implant, Braces, and Crowns are highly reliable, while Nerve Involvement and Sinus Involvement show perfect metrics, though lacking AUC and P-values, suggesting the need for further validation. All tests have statistically significant P-values (<0.0001). Overall, these results underscore AI's potential as a reliable, complementary tool for clinical dental diagnostics.

In the realm of oral diagnosis, AI has proven to be a game-changer. AI algorithms can assist dentists in detecting and diagnosing a wide range of oral conditions, from dental caries and periodontal disease to oral cancer lesions**. [10]** One key advantage of AI in this context is its ability to automate the detection of early-stage conditions, enabling quicker diagnosis and potentially improving patient outcomes. For instance, AI can identify subtle radiographic features that might be missed by human observers, especially in cases of early caries or bone loss. [11] This increases the efficiency of dental clinics by allowing professionals to focus more on treatment rather than spending time on diagnosis.

The benefits of AI-driven oral diagnosis extend beyond the clinical setting, as it can also contribute to improved practice management and cost-effectiveness. By automating routine tasks and streamlining diagnostic processes, AI can help dentists optimize their workflows, reduce administrative burdens, and allocate resources more efficiently.

The effectiveness of AI extends beyond diagnostics into patient education. AI in dentistry has transformative potential, particularly in enhancing patient engagement, comprehension, and satisfaction through innovative technological solutions. The main barriers to effective communication in healthcare include limited time for consultations, financial incentives that prioritize treatment over prevention, inadequate training in oral health literacy (OHL), a lack of patient education materials in simple language, and difficulties in engaging patients who have low OHL proficiency. [12] Studies have shown that when patients are more informed about their diagnosis, they are more likely to comply with recommended treatment plans**.[13]**

AI’s role in analyzing OPGs and intraoral images thus not only improves diagnostic accuracy but also empowers patients to make informed decisions about their oral health, ultimately contributing to better overall treatment outcomes. The integration of AI in dental practices is expected to continue expanding, offering both clinicians and patients a more efficient, patient-centred approach to oral healthcare. **[14]**

Despite their potential, AI advances are however to have a noteworthy effect in therapeutic hone. CNNs in dentistry are being created**. [15]** Handling certain issues will offer assistance to create dental AI innovation superior and encourage their take-up in clinical care. For interpretation dentistry uses imaging data which is frequently collected over a period of time.

4 | CONCLUSION:

AI is revolutionizing dentistry by offering advanced tools for diagnosing a variety of dental conditions. AI-driven algorithms, trained on large datasets of radiographs and intraoral images, can quickly and accurately identify patterns, enhancing diagnostic precision. Using deep learning models like convolutional neural networks (CNNs), AI can assess complex dental structures, supporting the detection of caries, impacted teeth, fractures, root stumps, and more. In this study, a dentist independently verified AI-detected conditions, with statistical analyses showing high sensitivity, specificity, and AUC values for most conditions, confirming AI's diagnostic reliability. AI not only improves clinical efficiency by reducing diagnostic time but also aids in patient education, helping individuals better understand their diagnoses and treatment options. Additionally, AI streamlines practice management by automating routine tasks, optimizing workflows, and reducing administrative burdens. However, barriers remain, such as limited consultation time and the need for simpler patient education materials. Despite these challenges, AI’s potential in dentistry continues to expand, supporting a more efficient, patient-centred approach to oral healthcare and paving the way for further advancements in diagnostics and patient engagement. AI models have the potential to be a valuable instrument for diagnosing caries and tooth dysfunctionality. The dental applications of AI models, on the other hand, are still within the works. Ongoing research and collaboration are crucial for fully realizing AI’s potential in transforming oral healthcare. To propel AI advancements in dentistry, future studies must address current limitations, enhance data quality, expand datasets, and focus on creating more interpretable AI models. Long-term clinical studies are essential to evaluate the safety, effectiveness, and cost-efficiency of AI tools. Furthermore, ethical considerations such as transparency, accountability, and fairness need to be embedded in the development and application of AI systems in dentistry. With sustained research, cooperation, and thoughtful integration, AI can revolutionize dental care and significantly improve patient outcomes.

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