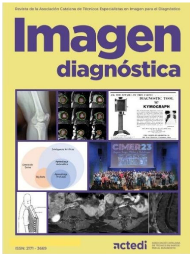

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Artificial Intelligence-Assisted Panoramic Radiography for Detection of Mandibular Cortical Changes in Dental Patients

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Abstract: Background: Panoramic radiographs may show mandibular cortical thinning and erosion, which could reflect changes in the skeletal bone status but it is subjective and time consuming to routinely assess these changes visually. The aim of this study was to assess the diagnostic accuracy of an Artificial Intelligence (AI) supported panoramic radiography system for detecting changes in the mandibular cortex in adult dental patients. **Methods:** A cross sectional diagnostic accuracy study was performed on 180 adults who were referred for digital panoramic radiography for routine dental indications. The reference standard was set by two blinded oral and maxillofacial radiologists, who used the Mandibular Cortical Index (MCI) and the Mandibular Cortical Width (MCW). Cortical change was defined as MCI C2/C3 or MCW <3.0 mm on either side. An AI model was used to segment the bilateral mental foramen-inferior cortex regions, classify MCI, measure MCW and calculate a patient-level probability score. **Results:** Sixty-one patients (33.9%) had mandibular cortical changes identified by expert consensus. Patients with cortical changes were older than those without changes (61.7±10.8 vs. 48.2±13.9 years; p<0.001) and had lower mean MCW (2.64±0.36 vs. 3.82±0.54 mm; p<0.001). The AI system had a sensitivity of 88.5%, specificity of 90.8%, accuracy of 90.0%, positive predictive value of 83.1%, negative predictive value of 94.0% and area under the receiver operating characteristic curve of 0.94. There was good agreement between AI and expert classification of MCI (weighted kappa = 0.78) and excellent agreement for MCW measurement (ICC = 0.89). The time to interpret using AI was substantially less than the time to interpret using general dentist visual assessment (12.4±3.1 seconds vs. 82.7±18.5 seconds; p<0.001). **Conclusion:** AI-assisted panoramic radiography showed high accuracy in detecting mandibular cortical changes and could be used to assist opportunistic screening and referral in dental settings but external validation and incorporation into clinical risk assessment is needed.

Key Words: Artificial Intelligence, Panoramic Radiography, Mandibular Cortical Index, Mandibular Cortical Width, Osteoporosis Screening, Dental Radiology

INTRODUCTION

Dental panoramic radiography is one of the most commonly used imaging techniques in routine dental practice, as it offers a wide view of teeth, jaws, temporomandibular areas and surrounding maxillofacial structures at a relatively low radiation dose. In addition to dentoalveolar pathology, panoramic radiographs can provide clinically relevant information regarding the status of the entire body skeleton, especially the inferior cortex of the mandible in the region of the mental foramen. Guidelines for use of panoramic radiographs in osteoporosis screening stress that dental radiographs should not be used as a substitute for DEXA but may be used to identify patients who may need medical referral if there are radiographic signs of cortical thinning or erosion [1].

Mandibular cortex is sensitive to age-related and systemic alterations in bone remodeling. The Mandibular Cortical Index (MCI) categorizes the lower mandibular cortex as normal (C1), mildly to moderately eroded (C2) or severely eroded/porous (C3) while the Mandibular Cortical Width (MCW) gives a quantitative assessment of the thickness of the lower mandibular cortex below the mental foramen. One of the key benefits of these indicators is that they can be evaluated from existing dental diagnostic radiographs, thereby providing a chance for sustainable and opportunistic screening without extra imaging exposure or cost [2].

Systematic review evidence has demonstrated that some panoramic radiomorphometric measurements (such as MCW and MCI) are linked to low BMD and may be useful in identifying the individuals who need additional skeletal evaluation [3]. In postmenopausal women, MCI has been reported to be a helpful auxiliary screening tool, as in women with more advanced cortical erosion, the bone mineral density of the skeleton is lower [4]. Previous diagnostic research also showed that the presence of eroded or thin mandibular cortices on panoramic radiographs can be used to identify younger postmenopausal women who are at risk for low bone mineral density or osteoporosis, thus making dentists a potential part of the early medical referral pathway [5].

Although these benefits are present, clinical use is not consistent. Visual grading of MCI is dependent on the experience of the observer, radiographic contrast, magnification, patient positioning and overlap of anatomical structures. Although some studies have shown that quantitative MCW measurement is more reproducible than visual grading, manual measurement still requires precise localization of the mental foramen and inferior cortex. The use of chairside information combined with panoramic measurements can increase the diagnostic accuracy but manual interpretation of panoramic measurements is difficult in the busy dental outpatient environment [6].

In the field of dentistry, AI, especially deep learning using convolutional neural networks, has been highlighted as a potential solution for automating image interpretation tasks. Discrimination of osteoporosis from dental panoramic radiographs has been reported using transfer learning with deep convolutional networks [7] with promising results. The combination of radiographic features with clinical covariates in ensemble deep learning models has also been shown to improve the classification performance for osteoporosis risk when using panoramic radiographs [8]. The research indicates that AI could help minimize inter-observer variability and offer consistent decision-making assistance for dental practitioners.

AI techniques for prediction and identification of osteoporosis using MCI have been specifically evaluated in recent studies. Multiple CNN models were compared and it was found that deep learning can be used to identify MCI patterns in panoramic radiographs that are associated with osteoporosis [9]. More recent studies have shown the potential of AI for the identification of osteoporosis on dental panoramic radiographs but also noted methodological limitations, including the size of the datasets, selection bias and the need for independent validation [10].

While AI models for osteoporosis screening have been explored, fewer clinical studies have assessed the use of AI as a diagnostic tool for detecting mandibular cortical changes in general dental patients where the dental question at hand is not necessarily related to bone health. This is significant because routine dental populations contain images of varying quality, dentate and partially edentulous patients and men and women. Thus, it is essential to evaluate the performance of AI systems in comparison with the consensus of expert radiologists in a realistic dental radiology workflow before recommending their use in the chairside setting.

The purpose of the present study was to assess the diagnostic accuracy of an AI-based panoramic radiography system for detecting changes in the mandibular cortex in adult dental patients. Secondary aims included comparing the performance of AI with that of the general dentist's visual assessment, quantifying the agreement between AI and expert radiologist measurements and examining demographic and dental factors that were associated with radiographic cortical changes.

METHODS

The Design and Setting of the Study

The study was a cross sectional diagnostic accuracy study carried out in the dental radiology unit of a tertiary dental teaching hospital from January to December 2025. The purpose of this study was to assess an AI-assisted panoramic radiography system in a typical outpatient imaging setting. All radiographs included were taken for clinical indications including missing teeth, general oral examination, impacted tooth evaluation, prosthodontic planning and periodontal evaluation. No panoramic radiograph was taken for the sole purpose of research.

The study was designed as a diagnostic accuracy study with the consensus of the expert oral and maxillofacial radiologists as the reference standard. This was used as the standard for the AI system and general dentist assessor. Patient identifiers were stripped off prior to image analysis and all image evaluations were made on coded radiographs.

Participants

The adult dental patients were sampled consecutively to include a total of 180 patients. Participants included those with a digital panoramic radiograph that included the bilateral mental foramen region and inferior mandibular cortex and were 18 years or older with a diagnostically acceptable image. Patients with a history of mandibular fracture or orthognathic surgery, a large cystic or neoplastic lesion of the mandible, metabolic bone disease under active investigation, long-term head and neck radiotherapy, severe image distortion, motion artifact obscuring the mandibular cortex and incomplete demographic data were excluded.

A diagnostic accuracy design was used to determine the sample size. With an assumed sensitivity of 85%, a precision of 9%, a 95% confidence level and an expected prevalence of cortical change of about 30%, a minimum of 170 participants was needed. The final sample of 180 was chosen to account for any images that might not be evaluable.

Radiographic Acquisition

Standardized panoramic unit and trained radiographers were used to obtain digital panoramic radiographs. Patients were seated on the chair as per the manufacturer's recommendations, aligned with the horizontal plane of Frankfort, centered with the mid-sagittal plane, stabilized with bite blocks and instructed to position the tongue against the palate. The exposure parameters were set automatically depending on the patient size and varied from 64-74 kVp and 6-10 mA. Images were exported in DICOM format and anonymized high resolution grayscale images for observer review and AI analysis.

Prior to inclusion, image quality was assessed as good, acceptable or poor. Images that were not good or acceptable were not analyzed. Moderate but not obscuring dental metallic artifacts were kept to mimic normal clinical conditions.

Reference Standard Assessment

The mandibular cortex on both sides was evaluated independently by two oral and maxillofacial radiologists with over eight years of experience. The endosteal margin of the cortex was classified as C1 (even and sharp), C2 (semilunar defects or cortical residues) and C3 (heavy porosity and endosteal cortical residues). Bilateral measurements of MCW were taken at the mental foramen level with calibrated digital measurement software. Patient-level classification was done using the lowest of the two MCW values.

Disagreements in the MCI category or MCW threshold classification were resolved by the joint review of the images until consensus was reached and MCI C2 or C3 on either side and/or MCW <3.0 mm was defined as a change in the mandible. The radiologists were blinded to the AI output, general dentist assessment and clinical risk factors (except age and sex, which were not shown during image interpretation).

AI-Assisted Analysis

The AI system employed a two-stage process. The right and left mental foramen-inferior cortex regions of interest were first localized by a segmentation module. Second, a Convolutional Neural Network (CNN) classifier was used to classify MCI and provide a probability score for cortical change. A measurement module was developed to estimate MCW by means of the segmented inferior cortical boundary, following the pixel-to-millimeter calibration using the image metadata. The highest probability score on either side and the lowest MCW was used for each patient.

The AI model was trained in a separate institutional dataset of 1620 panoramic radiographs and validated on 240 panoramic radiographs, which were collected from other institutions. No radiograph from the present study was employed for training, tuning or threshold selection. The probability threshold for a positive output of a cortical change was prespecified at 0.50. AI output comprised MCI category, MCW measurement, probability score and heat-map localization for visual verification.

General Dentist Assessment

All anonymized radiographs were independently interpreted by one general dentist with five years of experience, for comparison with routine clinical visual interpretation, after a short calibration session. Each image was judged as normal or suspicious for mandibular cortical change by visual assessment of the degree of cortical thinning, erosion and porosity. The dentist was not aware of AI output and expert consensus.

Statistical Analysis

SPSS version 28 was used for data analysis. Continuous variables were presented as Mean±SD or median (IQR) and categorical variables were presented as frequency and percentage. Independent t-test or Mann-Whitney U test was used for continuous variables and chi-square test or Fisher exact test was used for categorical variables to compare the differences between the patients with and without expert-defined cortical changes.

The accuracy of the AI and general dentist assessments were determined by calculating sensitivity, specificity, positive predictive value, negative predictive value and overall accuracy. AI probability score was used for Receiver Operating Characteristic (ROC) analysis and the Area Under the Curve (AUC) was reported with 95% confidence interval. Weighted kappa was used to assess agreement between AI and expert MCI classification and Intraclass Correlation Coefficient (ICC) was used to assess agreement for MCW measurement. A p value of <0.05 was deemed to be statistically significant.

RESULTS

Participant Characteristics

Among 196 screened patients, 16 were excluded because of motion artifact (n = 7), obscured mental foramen region (n = 5), previous mandibular fracture fixation (n = 2) and incomplete clinical data (n = 2). The final analysis included 180 patients. The mean age was 52.8±14.6 years and 104 patients (57.8%) were female. Expert consensus identified mandibular cortical changes in 61 patients (33.9%).

Patients with cortical changes were significantly older than those without changes (61.7±10.8 vs. 48.2±13.9 years; p<0.001). Female sex was more frequent in the cortical change group (72.1 vs. 50.4%; p = 0.006) and postmenopausal status among women was also more common (65.9 vs. 38.3%; p = 0.004). Partially edentulous status and history of previous tooth loss were more frequent among patients with cortical changes, while current smoking did not differ significantly between groups (Table 1).

Radiographic and AI-Derived Findings

Expert consensus classified 119 patients (66.1%) as MCI C1, 42 patients (23.3%) as C2 and 19 patients (10.6%) as C3 at patient level. Mean MCW was significantly lower in patients with cortical changes than in those without changes (2.64±0.36 vs. 3.82±0.54 mm; p<0.001). The AI system produced higher cortical change probability scores in the cortical change group (0.81±0.17 vs. 0.18±0.14; p<0.001).

Table 1: Demographic and Clinical Characteristics According to Expert-Defined Mandibular Cortical Status

Variable	Total (n = 180)	No cortical change (n = 119)	Cortical change (n = 61)	p-value
Age (years)	52.8±14.6	48.2±13.9	61.7±10.8	<0.001
Female sex (n (%))	104 (57.8)	60 (50.4)	44 (72.1)	0.006
Body mass index (kg/m^2)	24.9±3.8	25.3±3.7	24.2±3.9	0.071
Postmenopausal women (n/N (%))	86/104 (82.7)	23/60 (38.3)	29/44 (65.9)	0.004
Current smoker (n (%))	28 (15.6)	17 (14.3)	11 (18.0)	0.512
Partially edentulous (n (%))	77 (42.8)	41 (34.5)	36 (59.0)	0.002
History of fragility fracture (n (%))	15 (8.3)	5 (4.2)	10 (16.4)	0.006
Image quality good (n (%))	139 (77.2)	94 (79.0)	45 (73.8)	0.426

Table 2: Radiographic and AI-Derived Mandibular Cortical Findings

Variable	Total (n = 180)	No cortical change (n = 119)	Cortical change (n = 61)	p-value
Expert MCI C1 (n (%))	119 (66.1)	119 (100.0)	0 (0.0)	<0.001
Expert MCI C2 (n (%))	42 (23.3)	0 (0.0)	42 (68.9)	<0.001
Expert MCI C3 (n (%))	19 (10.6)	0 (0.0)	19 (31.1)	<0.001
Lowest expert MCW (mm)	3.42±0.73	3.82±0.54	2.64±0.36	<0.001
AI-estimated lowest MCW (mm)	3.39±0.76	3.78±0.57	2.62±0.39	<0.001
AI cortical change probability	0.39±0.32	0.18±0.14	0.81±0.17	<0.001
AI heat-map localization acceptable (n (%))	169 (93.9)	112 (94.1)	57 (93.4)	0.852
AI analysis time (seconds)	12.4±3.1	12.1±3.0	12.8±3.3	0.146

Table 3: Diagnostic Performance Against Expert Radiologist Consensus

Method	TP	FP	FN	TN	Sens (%)	Spec (%)	PPV (%)	NPV (%)	Acc (%)	AUC (95% CI)
AI	54	11	7	108	88.5	90.8	83.1	94.0	90.0	0.94 (0.90-0.98)
Dentist	43	16	18	103	70.5	86.6	72.9	85.1	81.1	0.79 (0.72-0.86)
AI+dentist	57	21	4	98	93.4	82.4	73.1	96.1	86.1	0.88 (0.82-0.94)

TP: True positive, FP: False positive, FN: False negative, TN: True negative, PPV: Positive predictive value, NPV: Negative predictive value, AUC: Area under the curve

Agreement between AI and expert MCI classification was substantial (weighted kappa = 0.78; 95% CI, 0.69-0.87). Agreement for MCW measurement was excellent (ICC = 0.89; 95% CI, 0.85-0.92). Mean AI processing and reporting time was 12.4±3.1 seconds per image, compared with 82.7±18.5 seconds for general dentist visual assessment (p<0.001) (Table 2).

Diagnostic Accuracy

Using the prespecified patient-level probability threshold of 0.50, the AI system correctly identified 54 of 61 patients with cortical changes and 108 of 119 patients without cortical changes. This corresponded to sensitivity of 88.5%, specificity of 90.8%, positive predictive value of 83.1%, negative predictive value of 94.0% and overall accuracy of 90.0%. The AUC for the continuous AI probability score was 0.94 (95% CI, 0.90-0.98).

General dentist visual assessment showed lower sensitivity than AI (70.5% vs. 88.5%) but similar specificity (86.6% vs 90.8%). The net increase in detected cases with AI was 11 additional true positives per 180 examined radiographs, at the cost of four additional false positives compared with dentist assessment. In subgroup analysis, AI sensitivity remained above 85% in both women and men and in good and acceptable-quality radiographs.

Multivariable Analysis

In multivariable logistic regression including age, sex, partial edentulism, history of fragility fracture and AI probability score, the AI probability score remained the strongest independent predictor of expert-defined cortical change (adjusted odds ratio [aOR] per 0.10 increase: 1.72; 95% CI, 1.42-2.08; p<0.001). Age also remained independently associated with cortical change (aOR per 10 year increase: 1.58; 95% CI, 1.19-2.10; p = 0.002), while female sex showed a weaker but significant association (aOR: 1.96; 95% CI, 1.01-3.82; p = 0.047). Partial edentulism was not independently significant after adjustment (aOR: 1.42; 95% CI, 0.71-2.84; p = 0.321).

DISCUSSION

In the present study, AI-supported panoramic radiography was able to accurately identify the changes in the mandibular cortex in adult dental patients using the consensus of expert oral and maxillofacial radiologists as the reference standard. The AI system showed high sensitivity (88.5%), specificity (90.8%) and the AUC (0.94), which demonstrates good discrimination between normal and altered morphology of the mandibular cortex. The results of this study indicate that routine dental radiographs can be used for opportunistic detection of patients who may need additional skeletal evaluation but that the use of dental radiographs to make medical diagnoses is inappropriate.

The rate of expert-defined cortical change in this sample was 33.9%, a rate that is clinically reasonable for an adult dental outpatient population that is enriched with middle-aged and elderly patients. Patients with cortical changes were older, more commonly female, more commonly postmenopausal and more likely to have had a previous fragility fracture. These relationships are consistent with the biological hypothesis that thinning and erosion of the cortex are the result of cumulative bone remodeling, hormonal changes and systemic bone health. The lower mean MCW for patients with cortical changes supports the visual MCI classification of the expert panel.

Our AI accuracy is comparable to recent systematic evidence that deep learning models can attain high diagnostic accuracy for osteoporosis-related findings on panoramic radiographs. A systematic review of deep learning-based evaluation yielded pooled results that indicate the feasibility of using AI to interpret panoramic radiographs but also highlighted the variability of study design and data characteristics [11]. A second systematic review and meta-analysis found that AI, particularly deep learning, has high diagnostic accuracy for osteoporosis detection on panoramic radiography but with some limitations due to small study effects and methodological variation [12].

The present study builds on this evidence by examining changes in the mandible, rather than osteoporosis diagnosis per se. This is a significant difference. Panoramic radiography is not a good indicator of osteoporosis and mandibular indices are not a replacement for DXA. A recent meta-analysis of the mandibular radiomorphometric indices suggested that these indices can serve as screening tools for reduced BMD but cannot be used as a single diagnostic tool [13]. Hence, the most suitable clinical application of AI in this context is to alert the clinician to suspicious findings of the mandibular cortex, which can then be reviewed by the clinician and medical referral made when combined with patient age, sex, fracture history and other risk factors.

The AI system was more sensitive than the general dentist visual assessment and had a clinically relevant decrease in false negatives. This is important because in general dental practice, the assessment of the mandibular cortex is not routinely highlighted in every panoramic interpretation. Human observers might only consider the patient's chief dental problem and might not systematically examine the inferior mandibular cortex. AI can offer a second reading that is consistent and identifies areas of interest in the anatomy and normalizes measurement. The higher number of false positives, however, compared to dentist assessment further emphasizes the need for clinician supervision and suitable referral levels.

There was a good level of agreement between AI and expert radiologists for MCI and excellent for MCW measurement. The higher level of agreement for MCW could be because linear measurement is an objective measurement, whereas the grading of cortical erosion is more categorical and subjective in nature. This facilitates the utilization of hybrid AI outputs with both a probability score and interpretable measurements. A further advantage of heat-map localization is that it can help to increase trust by indicating whether the model was based on the anatomically plausible regions of the cortex or irrelevant image artifacts.

AI interpretation had a significant time benefit. The time it took for Mean AI to analyze the images was about 12 seconds, while the general dentist visual assessment took over one minute. Automated pre-screening might thus help streamline workflow in high-volume outpatient dental radiology without significantly increasing the reporting workload. Dental clinics could be an opportunity for the identification of risk in patients who may not otherwise have been evaluated for medical bone health, from a public health perspective.

The study also emphasizes the challenges of implementing AI in dentistry at a broader level. The literature has highlighted the potential of AI in dental diagnosis, treatment planning and research, yet there are challenges related to the implementation of AI in dentistry, such as the need for transparency, validation, clinician training and clear medico-legal responsibility [14]. Factors like data protection, compatibility with current software, confidence in model results, expense and accountability concerns can affect adoption in dental clinics [15]. These barriers can be mitigated when using AI as decision support instead of a diagnosis for mandibular cortical screening.

There are a number of caveats. First, this was a single-center study with a moderate sample size and performance may vary with other panoramic machines, image acquisition protocols, ethnic groups and dental population profiles. Second, the reference standard for cortical changes was expert radiologist consensus, which DXA was not available for all participants and therefore the study is not a diagnosis of osteoporosis. Third, the AI model was trained on an institutional dataset but it has not been validated on study images; it needs to be externally validated. Third, the use of routine-quality radiographs may not be sufficient to interpret the image in partially edentulous areas, metallic restorations and variations in patient positioning.

Further studies are needed to assess multicenter data, prospective AI workflow, comparison to DXA results, calibration across panoramic devices and incorporation with clinical risk tools. Further studies are needed to identify if AI-generated alerts enhance the right medical referral without unnecessary investigations and overloading healthcare systems. A pragmatic approach might be to use AI to identify cortical changes, then confirm by the dentist, document clinical risk factors and refer for medical evaluation if there is a match between the radiographic and clinical findings.

In conclusion, the current results indicate that AI-supported panoramic radiography could be a useful tool for the diagnosis of changes in the mandibular cortex in dental patients. When used responsibly in a clinician-supervised model, the technology could help to enhance consistency, minimize the loss of radiographic signs and provide a link between dental imaging and systemic health screening.

CONCLUSIONS

The diagnostic accuracy of AI-assisted panoramic radiography was very high in detecting mandibular cortical changes in adult dental patients compared with the consensus of expert radiologists. The system demonstrated good agreement for classification of the mandibular cortical index, excellent agreement for the measurement of the cortical width and quicker interpretation than routine visual assessment. The results of this study provide further evidence for the use of AI as a screening tool for bone health that can be used in conjunction with a clinician's assessment. Before widespread clinical use, external validation, DXA-correlated studies and standardized referral protocols are needed.

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