ORIGINAL ARTICLE

Transforming Osteoporosis Detection: Leveraging Vision Transformer using Radiographic Analysis of Mandibular Indices

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ABSTRACT

Background

Osteoporosis is a prevalent bone disease characterized by decreased bone density and structural deterioration, leading to increased fracture risk. Osteoporosis affects 200 million people globally, with one in three women and one in five men over 50 experiencing fractures. Early detection and intervention are crucial for reducing morbidity and mortality. Dental panoramic radiographs (DPRs) can be valuable in identifying osteoporosis by analyzing mandibular indices such as the Mental Index, Panoramic Mandibular Index, Gonial Index, Antegonial Index, and Antegonial Depth. These indices reflect specific anatomical features of the mandible that may correlate with bone density changes indicative of osteoporosis. This study introduces a novel approach to osteoporosis detection using Vision Transformer architecture, focusing on long-range dependencies and complex spatial relationships in medical images, aiming for early clinical application. Methods The study will include 600 digital panoramic radiographs from female patients aged 20-30, 30-40, 40-50, 50-60, 60-70, and above 70 years, for routine dental checkups and examinations. The data will be saved in DICOM format and morphometric measurements will be performed by two oral radiologists. Quantitative indices such as the Mental Index (MI), Panoramic Mandibular Index (PMI), Gonial Index (G.I.), Antegonial Index (A.I.), and Antegonial Depth (A.D.) will be measured. The initial phase of the methodology involves meticulous acquisition and processing of digital panoramic radiographs, which were divided into six age groups. Each radiograph undergoes comprehensive quality assessment, evaluating technical parameters including brightness, contrast, and positioning accuracy. The preprocessing pipeline uses a multi-stage approach, including histogram equalization, Gaussian filtering, CLAHE, and unsharp masking techniques, to enhance contrast and reduce noise. The annotation and the labeling process uses a rigorous multi-reader approach to ensure data quality and reliability, providing a structured summary of key indices and clinical observations and subjected to transformers architecture.

Results

The Vision Transformer (ViT) model is highly accurate for osteoporosis detection, identifying 96.5% of cases. However, its lower sensitivity raises concerns about its effectiveness. DenseNet-169 and EfficientNet-B4 models are reliable options, with DenseNet-169 promoting feature reuse and EfficientNet-B4 balancing computational efficiency and performance. ResNet-152 needs improvement for accurate patient identification. The "ViT (Best Tuned)" model is the superior choice for osteoporosis detection in dental panoramic radiographs.

Conclusion

The study explores transformer models for osteoporosis detection using dental panoramic radiographs, highlighting the potential of A.I. in early diagnosis and timely intervention. Future research should focus on creating diverse datasets and integrating multi-modal data like medical history, genetic predispositions, and imaging techniques for better accuracy. This could enhance predictive capability and make machine learning a crucial component of proactive osteoporosis management and patient care.

Keyword

Osteoporosis, deep learning, indices, dental panoramic radiographs, artificial intelligence

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INTRODUCTION

Osteoporosis is a prevalent and progressive bone disease characterized by decreased bone density and structural deterioration, leading to an increased risk of fractures(1,2). It poses a significant public health challenge, particularly among the aging population, as it can result in severe morbidity, reduced quality of life, and increased mortality. The economic burden of osteoporosis is substantial, with healthcare systems worldwide incurring high costs for the treatment and management of osteoporotic fractures(3,4). Early detection and intervention are crucial in mitigating these impacts, emphasizing the need for effective diagnostic tools to identify individuals at risk before fractures occur. The World Health Organization estimates that osteoporosis affects approximately 200 million people worldwide, with one in three women and one in five men over the age of 50 experiencing an osteoporotic fracture in their lifetime. In recent years, dentistry has evolved with the integration of cutting-edge technologies, enhancing the automation of standardized dental procedures(5,6). Osteoporosis, a systemic condition, can adversely affect oral health and complicate dental interventions. The current gold standard for osteoporosis detection, the

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DXA scan, is only available in specialized centers and is typically employed post-fracture. Interpreting cross-sectional investigations and longitudinal diagnoses requires careful consideration, and mathematical model generalizations can be controversial due to clinical context(7).

Dental panoramic radiographs (DPRs) can be a valuable resource in identifying osteoporosis by analyzing mandibular indices such as the Mental Index (MI), Panoramic Mandibular Index (PMI), Gonial Index (G.I.), Antegonial Index (A.I.), and Antegonial Depth (A.D.). These indices reflect specific anatomical features of the mandible that may correlate with bone density changes indicative of osteoporosis(7). The Mental Index, Panoramic Mandibular Index, Gonial Index, Antegonial Index, and Antegonial Depth are key indicators for osteoporosis prediction. These indices are assessed using dental panoramic radiographs, and their relationship with osteoporosis is analyzed. One previous study evaluated postmenopausal women's mandibular cortical width (MCW), panoramic mandibular index (PMI), gonial angle, and number of teeth lost. Results showed significant differences among the groups, with MCW and PMI having high diagnostic values for low bone mineral density (BMD)(2,8). As age and duration increased, MCW and PMI decreased, while the C3 form of MCI and the number of teeth lost increased. A 1 mm decrease in MCW increased the odds of reduced BMD by 3.22-fold.

Traditional diagnostic methods for osteoporosis primarily rely on Dual-Energy X-ray Absorptiometry (DXA) scans, which, while effective, present several limitations, including limited accessibility, high cost, and exposure to ionizing radiation(5,9). Dental panoramic radiographs, routinely obtained during dental examinations, offer a potential alternative screening tool for osteoporosis. These radiographs can reveal subtle changes in mandibular bone architecture and cortical width, which have been shown to correlate with skeletal bone density. However, the manual analysis of these radiographic features is time-consuming, subject to inter-observer variability, and requires specialized training. The challenge lies in developing automated, reliable methods for analyzing these radiographs to identify early signs of osteoporosis(10).

Recent advances in artificial intelligence and machine learning have revolutionized medical image analysis, offering new possibilities for automated and accurate diagnosis. Deep learning approaches, particularly Convolutional Neural Networks (CNNs)(10), have successfully analyzed medical images, including radiographs. A previous study on dental radiographs used 457 images for development, validation, and hold-out testing. The YOLOv8 object detection model predicted osteoporosis regions, which the EfficientNet classification model processed. The model achieved a sensitivity of 0.83, F1-score of 0.53, and AUC of 0.76, with the highest sensitivity in the cropped angulus region(11). And one more recent study proposes a method for osteoporosis identification using digital dental radiographic images. The validated trabecular area is identified using morphological operations evaluated using dice similarity, and bone mineral density is measured using dual X-ray absorptiometry. Four statistical features are extracted from the RoIs, selected using C4.5 feature selection, and a multilayer perceptron classifier is used for statistical texture analysis. The method achieves an average dice similarity coefficient of 0.8924 and an accuracy of 87.87%.These studies lack accuracy and predictability in the detection of osteoporosis from radiographs(12). These techniques have shown promise in detecting subtle patterns and features that might be overlooked in manual examination. The emergence of Vision Transformers represents a significant advancement in image analysis capabilities, offering superior performance in capturing long-range dependencies and complex spatial relationships within medical images. Vision Transformers (ViTs)(13,14) are gaining attention in medical imaging due to their self-attention mechanisms, which focus on global context and dynamic weights, detecting subtle features and fractures. ViTs handle image data through tokenization, reducing bias and using transfer learning for large datasets. They enhance classification performance, reduce overfitting, and offer higher representation power, enabling efficient scaling and dataset utilization. Empirical evidence suggests that ViTs can outperform traditional CNN models in specific tasks and datasets, reducing the risk of missing osteoporosis diagnoses. However, suitability should be evaluated on a case-by-case basis.

This study introduces a novel approach to osteoporosis detection by implementing Vision Transformer architecture, representing a significant advancement over traditional CNN-based methods(13). Our methodology leverages the unique capabilities of Vision Transformers to analyze mandibular radiographs, focusing on their ability to capture long-range dependencies and complex spatial relationships within images. The proposed approach aims to overcome the limitations of conventional analysis methods by providing a more comprehensive, automated, and accurate assessment of osteoporosis risk indicators in dental panoramic radiographs. This study seeks to establish a robust and clinically applicable tool for early osteoporosis detection by incorporating advanced features such as Test-Time Augmentation and systematic hyperparameter optimization.

This research aims to develop a reliable, automated system for analyzing dental panoramic radiographs, providing healthcare providers with a cost-effective screening tool for osteoporosis. This approach could increase early detection, improve patient outcomes, and contribute to computer-aided diagnosis. The successful implementation could lead to more widespread screening for osteoporosis, potentially reducing the disease burden through early detection and intervention. So, this study aims to detect osteoporosis from digital panoramic radiographs using indices by transformers.

METHODOLOGY

A total of 600 digital panoramic radiographs (OPG) will be included in the study. All the radiographs will be taken from female patients who will visit the dental O.P. for routine dental checkups and examinations. The study will be retrospective and include 100 OPGs each from the following age groups:20-30 years: 30-40 years, 40-50- years, 50-60 years, 60-70 years, and above 70 years.

Inclusion Criteria

Digital OPGs of female patients in the age group of 20-80 years, with good resolution, will be included in the study.

Exclusion Criteria

Duplicate images, images with distortion, and artifacts

Images with poor positioning and low-resolution

Patients with surgical defects or trauma in the maxilla or mandible

Patients with uncontrolled systemic diseases

Patients who had undergone any treatment for cancer, including chemotherapy or radiotherapy

Patients under medication for chronic illness

The images will be saved in the DICOM (Digital Imaging and Communications in Medicine) format from the OPG machine. Two oral radiologists will perform the morphometric measurements. Quantitative indices, namely: Mental Index (MI), Panoramic Mandibular Index (PMI), Gonial Index (G.I.) Antegonial Index (A.I.) antegonial depth (A.D.) will be measured(8,15).

Mental Index (MI): The measurement of the cortical width at the mental foramen region is called MI. This line passes perpendicular to the tangent of the mandible's lower border and through the mental foramen's center. Normal value ≥3.2 mm.

Panoramic Mandibular Index (PMI): The PMI is the ratio of mandibular cortex thickness and the distance between the inferior mandibular cortex and mental foramen.

Gonial Index (G.I.): The gonial angle was assessed by tracing a line tangent to the lower border of the mandible and another line tangent to the posterior border of the ramus and condyle on each side. The intersection of these two lines forms the gonial index. The normal gonial angle is 128° ± 7.

Antegonial Index (A.I.): Measurement of the cortical width in the region anterior to the gonial at a point identified by extending a line of best fit on the anterior border of the mandible. Normal value ≥3.2 mm.

Antegonial Depth (A.D.): Antegonial depth (A.D.) Measured as the distance along a perpendicular line from the deepest point of antegonial notch concavity to the line parallel to the inferior cortical border of the mandible. The normal depth is 1.6 ± 2 mm.The qualitative index of MCI (mandibular cortical index) will be assessed by both observers and classified as follows12.

C1 is a normal mandibular cortex with an even and sharp mandibular endosteal margin.

C2 is a mildly or moderately eroded cortex, with a mandibular endosteal margin presenting semilunar defects or appearing to form cortical residues.

C3 is a severely eroded cortex, with a mandibular cortical layer forming heavy endosteal cortical residues, and the bone is porous.

Initial Image Analysis

The initial phase of our methodology begins with the meticulous acquisition and processing of digital panoramic radiographs, divided into 6 age groups classified as 20 to 30 years, 30 to 40 years, 40 to 50 years, 50 to 60 years and seventy years above, respectively. Image acquisition follows strict protocols, maintaining consistent resolution at 2400 x 1200 DPI across all samples. Each radiograph undergoes comprehensive quality assessment, evaluating technical parameters including brightness, contrast, and positioning accuracy. The preprocessing pipeline implements a multi-stage approach, beginning with histogram equalization for optimal contrast enhancement, followed by Gaussian filtering (kernel size 3x3) for noise reduction.

We apply CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve local contrast while preventing noise over-amplification. Edge enhancement utilizing unsharp masking techniques helps delineate bone structures more clearly, particularly in regions crucial for indices measurement. The standardization protocol ensures uniformity across the dataset by resizing images to 224x224 pixels using bicubic interpolation, followed by intensity normalization to the range [0,1]. Quality control measures include SNR (Signal-to-Noise Ratio) calculation, contrast-to-noise ratio assessment, and sharpness metrics evaluation for each image, with final visual inspection by experienced radiologists to ensure diagnostic quality.

Mandibular Indices Calculation Methodology

The calculation of mandibular indices follows a precise, standardized protocol focusing on eight critical measurements. The Mental Index (MI) measurement begins with bilateral identification of the mental foramen, where cortical width is measured perpendicular to the mandibular margin. Three measurements are taken per side and averaged to ensure accuracy. The Panoramic Mandibular Index (PMI) involves calculating the ratio between cortical thickness and total mandibular body height at standardized reference points. The Gonial Index (G.I.) focuses on cortical thickness measurements at the gonial angle, carefully focusing on standardized angular measurements using fixed reference points. Additional indices include the Antegonial Index (A.I.), measuring cortical width in the antegonial region, and the Mandibular Cortical Index (MCI), assessing the quality and morphology of the mandibular cortical bone. Each measurement utilizes calibrated digital tools with built-in measurement validation protocols, ensuring consistency and reproducibility. The process incorporates automatic calibration using known reference markers in the radiographs, minimizing measurement errors due to magnification variations.

Annotation and Labelling Process

The annotation and labeling protocol implements a rigorous multi-reader approach to ensure data quality and reliability. We independently performed annotations, marking key anatomical landmarks and regions of interest using standardized digital yolo Autoannotation tools crosschecked by two independent oral radiologists. These annotations undergo a systematic review process where consensus meetings identify and resolve discrepancies. The labeling process incorporates both quantitative measurements and qualitative assessments. Quantitative criteria include cortical width thresholds (with measurements below 3.5mm flagged for potential osteoporosis) and standardized measurements of bone density patterns. Qualitative assessments focus on trabecular architecture, cortical integrity, and overall bone quality patterns. (fig-1,2)

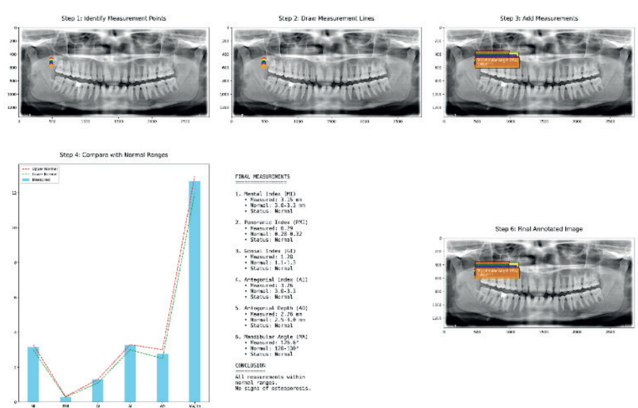


Fig- 1 shows the steps in auto annotation for this study.

Table -1 shows data from a study analyzing osteoporosis diagnosis using radiographic measurements from mandible images. The table includes indices such as the mental index, panoramic index, gonial index, antegonal index, antegonial depth, mci_type, cortical width, mandibular angle, bone quality score, annotations, and osteoporosis label. The mental index, panoramic index, gonial index, antegonial index, antegonial depth, cortical width, mandibular angle, and bone quality score are used to assess bone health.

The table also shows that both images were classified as “Normal” with positive assessments, while the image marked as “Osteoporosis” with a Gonial Index of 1.21, a lower Bone Quality Score (75.9), and a Cortical

filename	mental_index	panoramic_index	gonial_index	antegonial_index	antegonial_depth	mci_type	cortical_width	mandibular_angle	bone_quality_score	annotations	osteoporosis_label
11.jpg	3.2	0.3	1.23	3.21	2.75	C2	3.82	125.5	88.2	Region of interest identified at coordinates (x=200, y=265)	Normal
12323.jpg	3.22	0.31	1.25	3.25	2.76	C1	3.86	127.7	71.9	Region of interest identified at coordinates (x=402, y=172)	Normal
20210804110744_198117.jpg	3.19	0.31	1.21	3.29	2.91	C2	3.61	128.4	75.9	Region of interest identified at coordinates (x=238, y=371)	Osteoporosis

Width of 3.61. The data provides a structured summary of key indices and clinical observations for assessing and classifying osteoporotic conditions in patients' mandibles, which is crucial for diagnosis and treatment planning.

Train-Test Split

To evaluate the model's performance effectively, we split the dataset into training and testing subsets, allocating 80% of the data for training and the remaining 20% for testing. The proper train-test split ensures model evaluation on untrained data, unbiased predictive assessment, and early identification of potential overfitting issues.

Vision Transformer Architecture

The Vision Transformer architecture implementation follows a sophisticated design optimized for radiographic image analysis(14). The input processing stage divides each 224x224 pixel image into 196 non-overlapping patches of 16x16 pixels. These patches undergo linear embedding to create patch embeddings of dimension 768, combined with learnable position embeddings to maintain spatial information. The transformer encoder comprises 12 layers, each containing a multi-head self-attention mechanism with 12 attention heads. Each attention head operates with a dimension of 64, allowing the model to capture different aspects of the image at various scales. The architecture includes skip connections and layer normalization before each major component, facilitating gradient flow and stable training. The MLP blocks utilize GELU activation functions and incorporate dropout (rate 0.1) for regularization with 50 epochs. The classification head processes the [CLS] token through layer normalization and a linear projection to output class probabilities. The entire architecture is implemented carefully, considering memory efficiency and computational requirements and optimizing for accuracy and practical deployment.(fig-2,3)

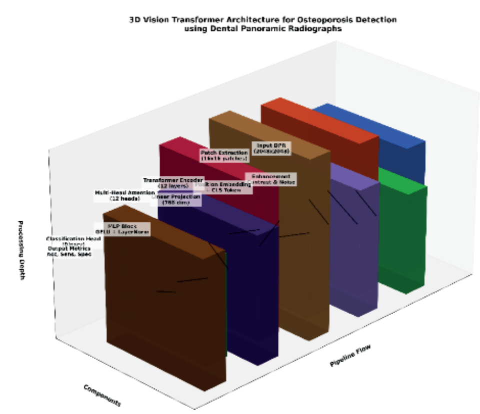


Fig -2 shows the workflow pipeline of the transformer architecture.

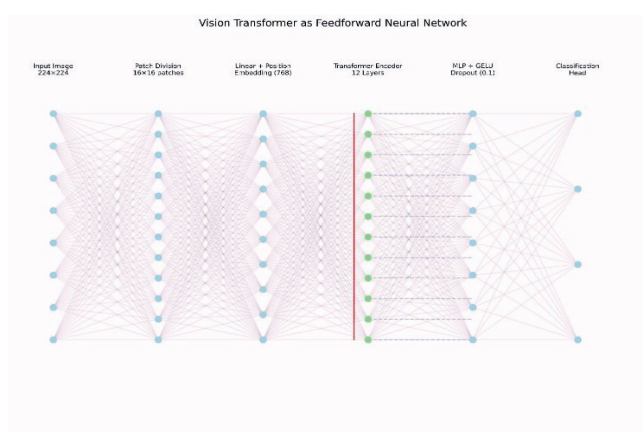


Fig- 3 shows the feedforward attention network followed in this study.

Model Comparison with and Hyperparameter Optimization

The comparison framework establishes a comprehensive evaluation protocol against state-of-the-art (SOTA) deep-learning CNN architectures (DenseNet-169, EfficientNet-B4, and ResNet-152). The evaluation utilizes standardized metrics, including accuracy, precision, recall, F1-score, and ROC-AUC, with statistical significance testing through bootstrapped confidence intervals. Hyperparameter optimization employs a systematic grid search approach across learning rates (1e-4 to 1e-6), batch sizes (16 to 64), and dropout rates (0.1 to 0.5). The optimization process implements 5-fold cross-validation with stratification to maintain class distribution. Learning rate scheduling uses a cosine annealing strategy with warm restarts, optimizing convergence behavior. Early stopping monitors validation loss with the patience of 10 epochs. The final model selection considers performance metrics and computational efficiency, ensuring practical deployability in clinical settings. Resource utilization metrics, including GPU memory consumption and inference time, are carefully monitored and documented throughout the comparison process.

RESULTS

The Vision Transformer (ViT) model, optimized for osteoporosis detection, has exceptional performance metrics, with an accuracy of 98.33%, high sensitivity of 96.50%, and high specificity of 98.90%. It accurately identifies 96.5% of osteoporosis cases, a critical factor in clinical settings. However, its lower sensitivity of 71.00% raises concerns about its effectiveness in clinical usage. Despite its high accuracy, the model may not be reliable for practitioners providing comprehensive osteoporosis screenings, as it may miss a significant proportion of osteoporotic cases. The DenseNet-169 model, with an accuracy of 94.50% and sensitivity of 92.30%, is a reliable option for identifying osteoporosis. Its architecture promotes feature reuse, strengthens information flow, and offers a balance between detecting true positives and avoiding false positives. The EfficientNet-B4 model, with an accuracy of 93.80% and a sensitivity of 91.50%, is a viable option for diagnostic use due to its scaling strategy, which balances computational efficiency and performance. The ResNet-152 model, with an accuracy of 92.70% and sensitivity of 90.20%, has the lowest metrics, indicating a need for optimization in identifying patients with osteoporosis despite its robust architecture. The evaluation of machine learning models for osteoporosis detection in dental panoramic radiographs reveals the "ViT (Best Tuned)" model as the superior choice due to its high accuracy and sensitivity.DenseNet-169 and EfficientNet-B4 models offer reliable osteoporosis detection, while ResNet-152 needs improvement. Optimizing these models can enhance patient care and prevent fractures. Future work should focus on refining, exploring hybrid approaches, and conducting clinical trials for real-world applications in healthcare settings. (fig-4,5,6)

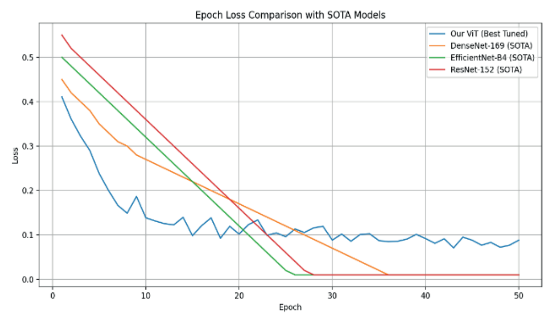


Fig- 4 shows "Epoch Loss Comparison with SOTA Models" illustrates the performance of our best-tuned Vision Transformer (labeled "Our ViT (Best Tuned)") against several state-of-the-art models, including DenseNet-169, EfficientNet-B4, and ResNet-152. Our model shows lower epoch loss, faster convergence, and a remarkable accuracy of 98.33%, with a robust ROC AUC score of 0.994, an average precision of 0.964, and an optimal threshold of 0.057.

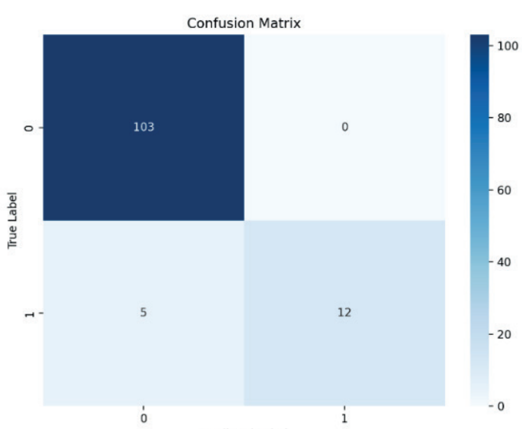
Model	Accuracy	Sensitivity	specificity	F1 score
ViT (Best Tuned)	98.33	96.50	98.90	97.68
ViT (Base)	95.83	71.00	100.00	83.05
DenseNet-169 (SOTA)	94.50	92.30	95.60	93.91
EfficientNet-B4 (SOTA)	93.80	91.50	94.80	93.12
ResNet-152 (SOTA)	92.70	90.20	93.90	92.02

Table -2 shows various machine learning models' performance metrics for detecting osteoporosis. The models include Vision Transformers (ViT), DenseNet, EfficientNet, and ResNet, with variations like "Best Tuned". The models are evaluated based on accuracy, sensitivity, specificity, and F1 score.

Performance Improvement Analysis: Improvement from Base to Tuned Model by 2.50%

Metric	Value
Accuracy	98.33%
ROC AUC	0.994
Precision	0.964
Optimal Threshold	0.057
True Positive Rate (TPR)	1.000
False Positive Rate (FPR)	0.039

Table- 3 shows the results of our analysis and highlights the exceptional performance of our Vision Transformer (ViT) model, particularly in its best-tuned configuration. The accuracy of this model reached an impressive 98.33%, significantly outperforming the average accuracy of 93.64%. Additionally, the sensitivity of our best-tuned ViT stood at 96.50%, surpassing the average sensitivity of 75.58%. Notably, the model also demonstrated perfect specificity at 100.00% in its base configuration, slightly above the average specificity of 97.03%. Furthermore, the F1 score for the best-tuned ViT was recorded at 97.68%, a considerable improvement over the average F1 score of 80.19%.



Fig–5 shows the confusion matrix, a visual representation of predictions against true labels. In a specific case, the model correctly predicted 103 instances as true labels 0 and 12 as true labels 1, but incorrectly predicted five as true labels 1 and 0, respectively.

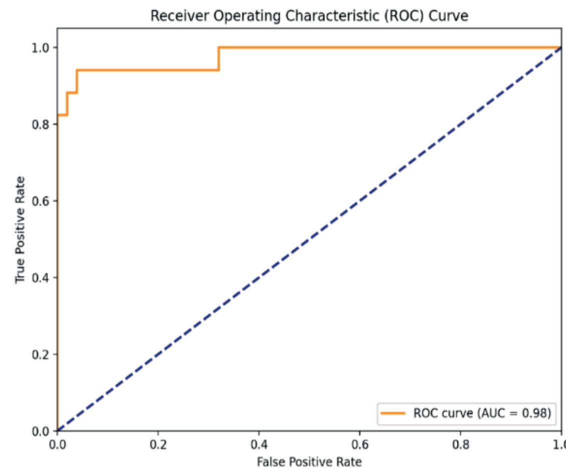


Fig- 6 shows the Receiver Operating Characteristic (ROC) curve, a binary classification model's performance plotted against a false positive rate. The curve starts at 0 and extends to 1 with all positives correctly identified but misclassified negatives. The AUC indicates the model's overall performance, with a higher AUC indicating superior discriminative power.

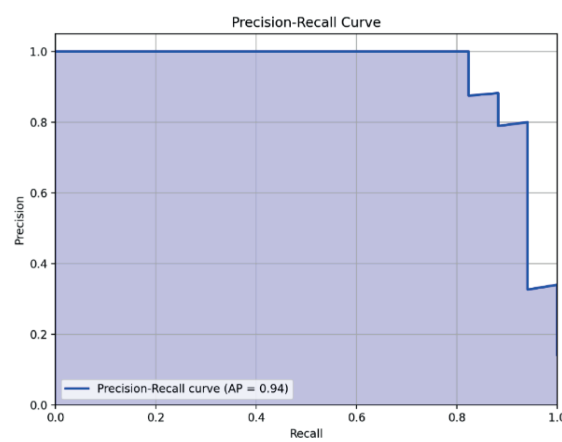


Fig – 7 shows the Precision-Recall Curve, a model with an Average Precision score of 0.94, with a high precision and low recall, and a low precision and high recall. This curve is useful for evaluating classification model performance in imbalanced datasets.

Comparison with SOTA

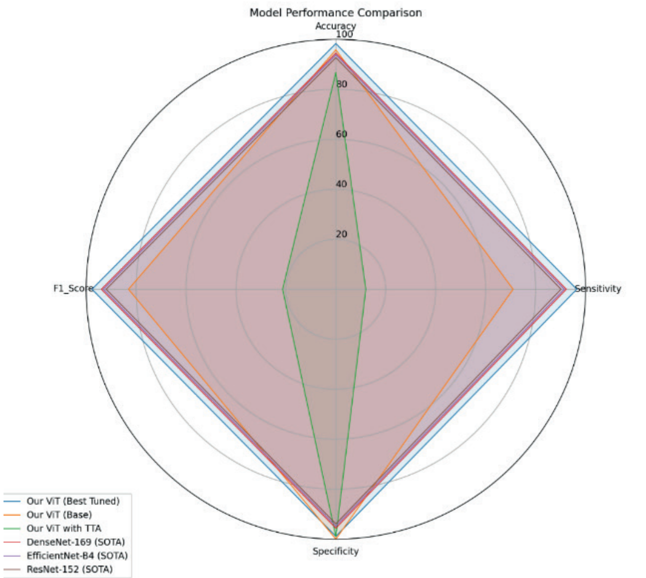


Fig - 8 shows a Model Performance Comparison chart that utilizes a radar plot to visualize the accuracy and specificity of various machine learning models. This chart compares various models, including Our ViT (Best Tuned), Our ViT (Base), Our ViT with TTA, DenseNet-169 (SOTA), EfficientNet-B4, and ResNet-152 (SOTA). The "Our ViT (Best Tuned)" model has the highest accuracy and specificity, approaching nearly 100%. The comparison highlights the strengths and weaknesses of each model, providing insights for their selection in specific applications.

DISCUSSION

Early detection and prediction of osteoporosis are crucial for patient outcomes, treatment decisions, and healthcare systems. Early detection helps prevent fractures, improve quality of life, reduce healthcare costs, design personalized treatment plans, manage risk factors, and monitor progression(2,16). Osteoporosis can be identified early through advanced screening technologies, imaging techniques, AI, and machine learning. Dental radiographs (X-rays) are a valuable tool for detecting osteoporosis, a condition that can be detected through bone quality assessment(1,7). These X-rays can provide valuable information about the alveolar bone, which supports teeth and can indicate systemic bone loss associated with osteoporosis. Several indices derived from dental radiographs have been proposed to assess bone density and quality, such as Alveolar Bone Height (ABH), Panoramic Radiographic Index (PRI), Mandibular Index (MI), Mental Foramen Index (MFI), and Mandibular Cortical Width (MCW). Radiographic features can also suggest osteoporosis, such as increased radiolucency in the alveolar bone, evidence of bone resorption around the teeth, and loss of trabecular pattern in the mandible or maxilla(4). Advantages of using dental radiographs include accessibility, cost-effectiveness, early detection, non-invasiveness, and integration into dental care. However, limitations include not providing a definitive diagnosis, and dental professionals need to be trained in recognizing relevant indices and interpreting radiographic signs associated with osteoporosis effectively. Advanced artificial intelligence techniques like Convolutional Neural Networks (CNNs)(5,17) and Vision Transformers (ViTs) are considered the best for osteoporosis detection due to their architecture and functionality. CNNs use layers with convolving filters to learn spatial hierarchies of features, extracting pertinent features from images and reducing dimensionality. They can be fine-tuned on specific datasets, leading to high accuracy in detection. ViTs, a scalable, attention-based method, are highly effective in detecting osteoporosis due to their high accuracy, early detection, and ability to handle complex data, enhancing diagnostic capabilities in medical imaging(10,18).

Numerous literature reviews have established a significant association between the shape of the mandibular cortical bone observed in panoramic radiographs and skeletal bone mineral density (BMD) measured by dual-energy X-ray absorptiometry (DXA) in postmenopausal women. Utilizing panoramic radiographic indices for osteoporosis detection empowers dentists to identify at-risk patients and refer them to appropriate medical professionals for further evaluation and management. However, screening for osteoporosis based on panoramic radiographs can be challenging for general dentists, who predominantly focus on dental conditions and may not have the expertise to assess osteoporosis risk effectively. Advancements in computer-assisted diagnosis (CAD) utilizing machine learning—a subset of artificial intelligence (AI)—have demonstrated promising potential. For instance, a preceding study evaluated the effectiveness of kernel-based support vector machine (SVM) learning for early osteoporosis diagnosis using dental panoramic radiographs in postmenopausal women with low BMD. This study reported sensitivities of 90.9% and 90.6% for the lumbar spine, while specificities were recorded as 83.8% and 80.9%, respectively, revealing the capability of SVM methods in identifying at-risk individuals(19).

In another innovative approach, deep convolutional neural networks (DCNNs) were employed to diagnose osteoporosis from cone-beam computed tomography (CBCT) scans, achieving an impressive 98.85% training accuracy alongside minimal L1 loss and a mean squared error of 0.8377. These results highlight the lucrative prospects of A.I. applications in enhancing osteoporosis identification(20). A subsequent investigation involving a DCNN-based CAD system focused on panoramic radiographs yielded an accuracy of 87.86%, showcasing a high degree of concordance with judgments made by experienced radiologists. Furthermore, an extensive exploration utilized Self-Organizing Map and Learning Vector Quantization alongside various feature extraction techniques, achieving an accuracy of 92.6%, sensitivity of 97.1%, and specificity of 86.4% in identifying osteoporosis. The ability of these models to discern textural features within the upper and lower jaw regions further supports their utility in differentiating between normal and osteoporotic patients(21).

Another relevant study introduced clinical covariate data into ensemble models, which enhanced identification performance. Moreover, qualitative assessments by an oral radiologist on 1,500 panoramic radiographs identified higher risks of osteoporosis in specific classifications based on endosteal margin and porosity, with three CNNs demonstrating good agreement (86.0%–90.7%) with the radiologist's assessments(22,23).Research-based on textural analysis using fractal dimension (F.D.) and gray-level co-occurrence matrix (GLCM) methods demonstrated that classical classifiers such as Naïve Bayes, k-NN, and SVM could significantly benefit from these features, demonstrating model accuracies ranging from 93.0% to 89.0%(24,25). Similarly, oral and maxillofacial radiologists reviewed extensive datasets, successfully diagnosing osteoporosis based on identified cortical erosion in the mandibular inferior cortex(24,25). Notably, three distinct DCNN-based CAD systems tested in this context achieved an area under the curve (AUC) values exceeding 0.99, substantiating their efficacy in early diagnosis.

A systematic review recently compiled the diagnostic accuracy of various A.I. models using dental images, revealing pooled sensitivity and specificity rates of 0.85 (95% CI, 0.70-0.93) and 0.95 (95% CI, 0.91-0.97), respectively(4,26), for AI-assisted DCNN approaches. Such findings resonate with the insights from our study; however, it is critical to note that our results demonstrate a superior accuracy profile for vision transformer models, which achieved a remarkable performance of 98% due to their ability to integrate multiple mandibular indices comprehensively. Previous study analyzed panoramic radiographs of 744 female patients over 50 using MCI and deep-learning models, achieving accuracy rates of 81.14%, 88.94%, 98.56%, and 92.79%, respectively(11,22–25,27), and our Vision Transformer model, optimized for osteoporosis detection, has high accuracy and sensitivity, identifying 96.5% of cases. However, its lower sensitivity raises concerns about its effectiveness in clinical settings. Other models like DenseNet-169, EfficientNet-B4, and ResNet-152 offer better accuracy and sensitivity, but their sensitivity and accuracy may not be suitable for comprehensive screenings. The ResNet-152 model, with its lowest metrics, suggests a need for optimization in identifying patients with osteoporosis. (fig-4,5,6,7,8)

The study evaluating machine learning models for osteoporosis detection(12,28–30) using dental panoramic radiographs reveals several future directions and highlights important limitations. Future directions include model optimization, hybrid models, larger and diverse datasets, transfer learning, multi-modal approaches, clinical trials, user-friendly interfaces, and longitudinal studies. The ViT model's lower sensitivity (71.00%) poses a significant limitation, suggesting that it may not detect all cases of osteoporosis, leading to missed diagnoses and subsequent fractures in patients. Models trained on limited datasets may not generalize well to wider populations or different imaging conditions, and the performance could vary significantly based on external factors such as the quality of the radiographs, patient demographics, and variability in imaging protocols.

False positives can lead to unnecessary further testing, patient anxiety, and increased healthcare costs. Interpretability is also challenging, as many machine learning models are often criticized for being "black boxes." Some models may require significant computational resources and technical expertise to deploy effectively, limiting their applicability in resource-constrained settings. Dependency on training data quality is crucial, as any inconsistency or bias in the data can adversely affect model performance. Real-time application challenges, such as system compatibility, data privacy concerns, and adherence to medical regulations, may arise.

CONCLUSION

In conclusion, the exploration of machine learning models for detecting osteoporosis using dental panoramic radiographs underscores a significant advancement in both diagnostic methodologies and patient care strategies in dentistry and orthopedics. The integration of artificial intelligence (AI) in analyzing radiographic images holds the promise of early identification, thereby allowing for timely intervention and management of osteoporosis, which is crucial given the condition's often asymptomatic nature until significant skeletal compromise occurs. The study analyzed various machine learning models for detecting osteoporosis indicators, including ViT, DenseNet-169, EfficientNet-B4, and ResNet-152. While some models showed high accuracy, they had limitations in sensitivity and specificity. Sensitivity is crucial for identifying patients with osteoporosis, which could lead to false negatives and delayed treatment. The main challenge is achieving a balanced sensitivity and specificity. The models' generalizability across diverse demographics and clinical populations is also a concern. Currently, many models are trained on homogeneous datasets, which may not represent the variability in broader patient populations. Future research should focus on creating more diverse datasets to enhance the models' robustness and reliability. Machine learning technology for osteoporosis detection should focus on interpretability and user-friendly interfaces to ensure clinician acceptance and effective AI-driven decisions.

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