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Expert Opinion Article

Comparative Evaluation Of Conventional Clinical Methods And Artificial Intelligence-Based Diagnostic Models In The Detection Of Chronic Generalized Gingivitis

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Abstract
Background:
Gingivitis is one of the most prevalent periodontal diseases worldwide, and early, accurate diagnosis is critical for preventing progression to irreversible periodontitis. While conventional diagnostic indices such as the Gingival Index (GI) and Plaque Index (PI) are widely used, they are inherently subjective and examiner-dependent. Recent advances in artificial intelligence (AI) offer promising alternatives for objective, scalable, and efficient periodontal diagnostics.
Aim:
To compare the diagnostic accuracy, sensitivity, and consistency of conventional clinical methods with an Artificial Neural Network (ANN)-based AI model in evaluating gingival health across a large population.
Materials and Methods:
An in vivo comparative study was conducted on 1,000 patients aged 14 to 75 years at a tertiary dental care institution. Gingival condition was evaluated using the GI and PI, and scored for color, contour, interdental papilla form, and presence of calculus. Standardized intraoral images were captured and analyzed using a trained ANN model comprising four specialized sub-networks. Diagnostic scores from AI and clinical methods were statistically compared using t-tests, ANOVA, correlation matrices, and reliability testing.
Results:
Conventional methods diagnosed gingivitis in 100% of patients with perfect inter-parameter consistency (Cronbach's $\alpha = 1.0$). The ANN model demonstrated high sensitivity (99.8%) and good internal reliability (Cronbach's $\alpha = 0.784$), particularly in detecting interdental papilla (accuracy: 74.91%) and calculus (accuracy: 80.47%). However, the AI system underperformed in identifying gingival color changes (accuracy: 70.78%; consistency: 63.42%) and showed weaker correlation in its provisional classification ($r = 0.044$). Significant statistical differences ($p < 0.001$) were observed across all diagnostic categories between AI and conventional methods.
Conclusion:
AI-assisted gingivitis detection demonstrates high sensitivity and consistency, especially for morphological parameters, and holds strong potential as an adjunctive tool in periodontal diagnosis. However, limitations in detecting early color changes and calculus suggest the need for algorithmic refinement and dataset expansion. AI models, when optimized and integrated with clinical workflows, may serve as scalable, objective complements to traditional diagnostic methods in both routine and community-based periodontal care.

Keywords: Gingivitis, Artificial Intelligence, Periodontal Diagnosis, Neural Network, Dental Imaging, Gingival Index, Plaque Index, Clinical Comparison

Introduction

Gingivitis is recognized as one of the most common and earliest forms of periodontal disease, affecting over 75% of the global population and ranking just behind dental caries in terms of prevalence. Its clinical and epidemiological importance stems from both its ubiquity and its potential for progression into more severe periodontal conditions. Epidemiological data suggests that nearly 87.4% of adults between 35 and 44 years of age exhibit gingival bleeding—one of the earliest signs of gingival inflammation—underscoring the silent yet widespread nature of this disease and the need for effective prevention, early diagnosis, and intervention strategies[1]. Gingivitis is characterized by inflammation confined to the gingival tissues without affecting the alveolar bone and periodontal ligament, making it a reversible condition if managed promptly. However, if left untreated, it may evolve into periodontitis—a destructive, chronic condition leading to the irreversible breakdown of supporting periodontal structures and eventual tooth loss.

The pathogenesis of gingivitis begins with the host's immune response to the accumulation of dental plaque, a complex biofilm composed of bacteria and salivary components[2]. This microbial accumulation at the gingival margin triggers an inflammatory cascade characterized by increased vascular permeability, vasodilation, and recruitment of immune cells, particularly neutrophils, to the gingival sulcus. Clinically, this inflammatory response manifests as erythema, edema, and bleeding on probing, while at the microscopic level, distinctive changes are observed in both epithelial and connective tissues. Disruption of the junctional epithelium is one of the earliest detectable changes, with cell junctions loosening to allow immune cells to infiltrate the gingival crevice[4]. Neutrophils form a temporary defensive barrier but also contribute to tissue damage through the release of reactive oxygen species and proteolytic enzymes[5]. Electron microscopy reveals additional structural alterations, including desmosomal detachment, cytoplasmic vacuolization, degeneration of keratinocytes, and fragmentation of the basal lamina[6]. In the connective tissue, macrophages and neutrophils secrete matrix metalloproteinases (MMPs), which enzymatically degrade collagen fibers—crucial for maintaining gingival integrity—while fibroblasts exhibit metabolic distress, impairing tissue repair mechanisms[6].

Vascular changes further compound the pathology of gingivitis. Dilated capillaries, thinning of endothelial basement membranes, and increased permeability result in the extravasation of plasma proteins and leukocytes, contributing to tissue edema and the characteristic reddened appearance of inflamed gingiva[7]. These pathological and ultrastructural features collectively correspond with the hallmark clinical signs—redness, swelling, bleeding on probing, and loss of stippling—reinforcing the diagnosis of gingivitis as a reversible inflammatory condition limited to superficial gingival layers[8]. Despite its reversibility, gingivitis often progresses insidiously and asymptomatically, which delays patient recognition and intervention, further stressing the need for timely and accurate diagnostic methods.

Prevalence data highlights gingivitis as a persistent public health burden. More than 42% of adults aged 30 and above show signs of gingival inflammation, while about 8% suffer from more advanced periodontal conditions[9]. The prevalence increases significantly with age, affecting nearly 60% of individuals aged 65 years and older, and is further complicated by systemic conditions such as diabetes mellitus and HIV, which increase susceptibility to gingival and periodontal disease[12]. Determining the exact burden of gingivitis remains challenging due to inconsistent diagnostic criteria across populations. Nonetheless, its presence is evident from early childhood, affecting 9–17% of children aged 3 to 11, and rising steeply in adolescence to 70–90%[10,12]. Globally, the trends mirror U.S. data, establishing gingivitis as an endemic oral health issue necessitating effective diagnostic and preventive strategies, particularly for vulnerable and underserved populations.

Traditionally, gingivitis is diagnosed using conventional clinical tools such as periodontal probing, the Silness and Löe Gingival Index, and the Plaque Index. These indices assess clinical signs like redness, swelling, and bleeding while quantifying plaque deposits[11,13,14]. Periodontal probing, often performed with a Williams probe, evaluates pocket depth and gingival integrity. Although clinically valuable, these methods are inherently subjective and require professional expertise, making them less effective for large-scale or community-level screenings[15]. Furthermore, diagnostic consistency is often compromised due to variations in examiner interpretation, and access to these tools remains limited in low-resource settings. Financial and infrastructural barriers also deter many from seeking regular dental evaluations, especially in developing regions.

In response to these limitations, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) algorithms, have emerged as promising tools for enhancing the objectivity and scalability of gingivitis diagnosis. AI-driven systems, especially those employing Artificial Neural Networks (ANNs), automate feature recognition in intraoral images, reducing human error and diagnostic variability while significantly improving time efficiency[16,17]. These models can analyze subtle gingival changes—such as color alterations, contour deviations, and papillary disruptions—that may elude traditional examination, thereby facilitating earlier detection and better treatment outcomes[17]. Moreover, AI allows for large-scale data processing, enabling community-level screening programs that are particularly beneficial in resource-constrained areas where access to specialized dental care is limited[18].

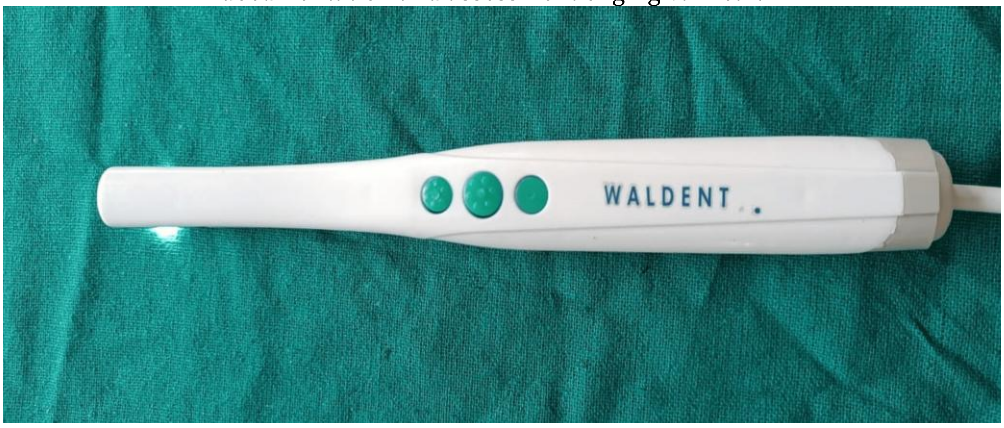
Importantly, AI models continue to evolve with expanding datasets, enhancing their diagnostic precision and adaptability in real time—a feature static clinical guidelines cannot offer[19]. Studies have shown that current AI-based systems exhibit diagnostic accuracies ranging from 0.47 to 1.00, with ≥0.90 considered clinically acceptable[20–22]. Several notable implementations have demonstrated the effectiveness of AI in dental diagnostics. For instance, the 2011 Fuzzy Expert System by Vijay K. and Anjali M.[24], ANN-based models for periodontitis detection by Georgios P. and Keiso T. in 2014[20], and the use of Extreme Learning Machines (ELMs) by Wen Y. et al. in 2018[25], collectively validate AI's capacity to surpass conventional techniques in efficiency and reliability.

Thus, the convergence of periodontal science with artificial intelligence opens a new chapter in gingivitis management. It offers a pathway toward standardized, rapid, and accessible diagnostic models that address the limitations of traditional clinical methods. In this evolving landscape, the adoption of AI not only enhances diagnostic precision but also democratizes oral healthcare by extending diagnostic reach across socioeconomic and geographic barriers. The following sections of this article will delve deeper into the comparative diagnostic performance of traditional methods and ANN-based models, underscoring the transformative potential of AI in the early detection and management of gingivitis.

Material & Methodology

FIGURE 1: Waldent® 5MP CMOS intraoral camera (Waldent Innovations Pvt. Ltd., India)

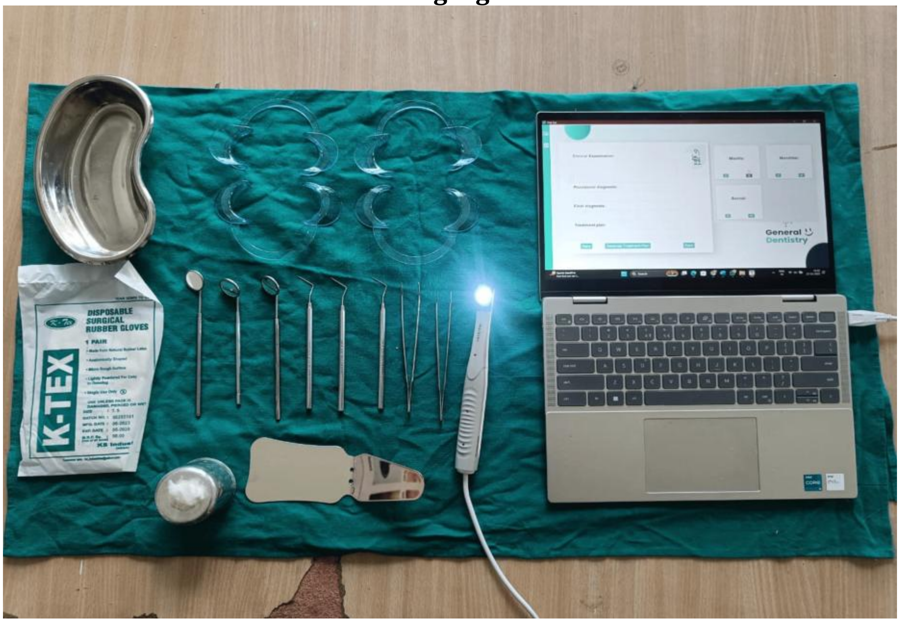
Intraoral image was obtained using the Waldent® 5MP CMOS intraoral camera (Waldent Innovations Pvt. Ltd.,India), a diagnostic device featuring a high-resolution 5-megapixel CMOS sensor and built-in LED illumination for enhanced intraoral visualization. The device supports real-time imaging and is used for accurate documentation and assessment of gingival health.



This comparative in vivo investigation was conducted over a span of one and a half years in the Department of Periodontology and Oral Implantology at NIMS Dental College and Hospital, Jaipur, Rajasthan, following institutional ethical clearance (Proposal No: IEC/P-240/2023) and has been registered under CTRI/2025/07/090873 for CTRI (clinical trial registration of India. The primary objective of the study was to assess and compare the diagnostic efficacy of conventional clinical indices and a machine learning-based artificial intelligence (AI) model for the detection of gingivitis. A total of 1,000 systemically healthy participants were recruited from the outpatient department through purposive sampling. Eligibility criteria included individuals aged between 14 and 75 years, irrespective of gender, possessing a minimum of 24 natural teeth and exhibiting clinical features consistent with gingivitis. Subjects presenting with systemic illnesses, those on chronic pharmacotherapy, individuals younger than 14 years, and those diagnosed with periodontal diseases other than gingivitis—such as periodontitis or necrotizing ulcerative conditions—were excluded to eliminate confounding variables. The sample size was calculated using a two-proportion formula, taking into account previously reported prevalence rates (Group 1: 45.98%, Group 2: 52.34%), with a statistical power of 80% and an alpha level of 0.05, yielding 500 participants per group.

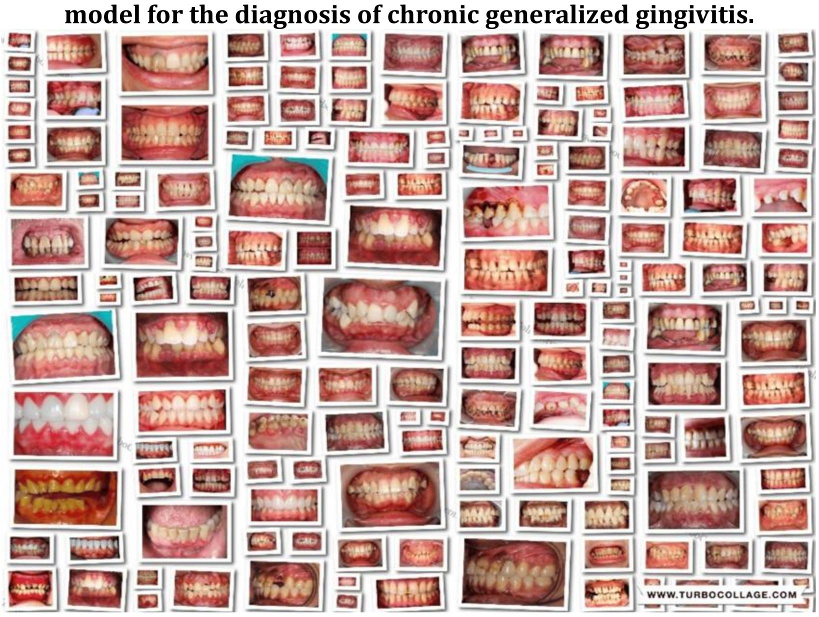
All enrolled patients underwent comprehensive periodontal examinations using standardized diagnostic armamentarium, including a Williams periodontal probe and mouth mirror. Gingival inflammation was assessed clinically through two well-established indices: the Gingival Index (Silness and Löe, 1963) and the Plaque Index (Löe and Silness, 1964). The Gingival Index was applied at four sites per tooth—mesial, distal, buccal, and lingual—using a scoring scale ranging from 0 (normal) to 3 (severe inflammation), while the Plaque Index evaluated the extent of supragingival plaque on a similar scale. Based on cumulative scores, each case was categorized as mild, moderate, or severe gingivitis. To complement clinical assessments, standardized intraoral photographs were captured using a Waldent 5MP CMOS autofocus intraoral camera under consistent lighting conditions, ensuring uniformity in image acquisition across subjects.(fig 1,2)

FIGURE 2: Armamentarium used includes 5MP CMOS Waldent Intraoral Camera, Artificial Neural Network Modelling algorithm



In parallel, the AI-assisted diagnostic modality utilized a pre-trained Artificial Neural Network (ANN) model specifically designed for gingival health assessment. The ANN had been developed using a dataset of 4,000 annotated intraoral images representing a spectrum of gingival conditions ranging from healthy to severely inflamed tissues, as well as sites exhibiting dental calculus.

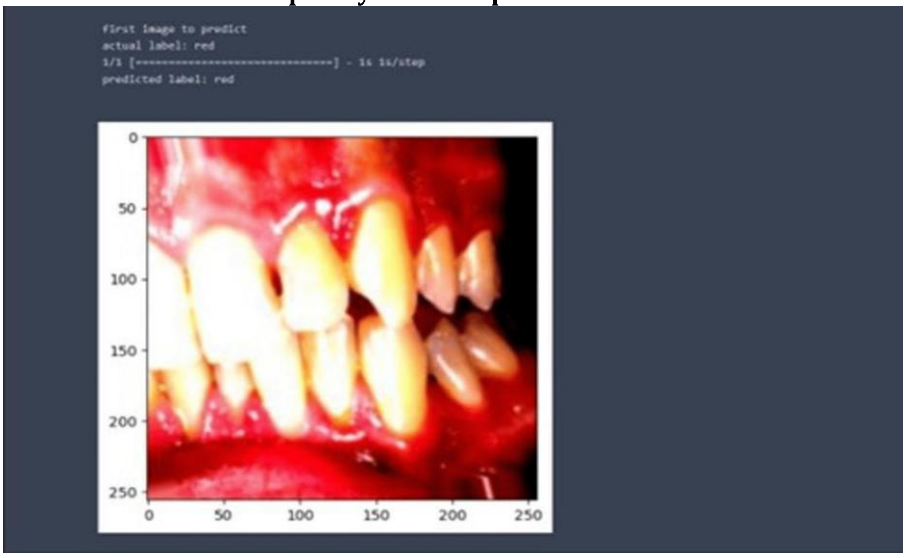
FIGURE 3: This collage presents a collection of clinical intraoral photographs depicting varying degrees of gingival health and inflammation. The images were used to train and validate an artificial intelligence model for the diagnosis of chronic generalized gingivitis.



Segmentation of the gingival region was performed using Canny edge detection and Otsu's thresholding techniques to isolate the region of interest (ROI) with high precision.

Subsequent feature extraction included HSV (Hue, Saturation, Value) transformation for color analysis, Fourier descriptors for contour profiling, and Gray Level Co-occurrence Matrix (GLCM) modeling for texture characterization, along with 3D surface curvature analysis.

FIGURE 4: Input layer for the prediction of label red.



The ANN framework comprised four specialized sub-models: Color_Model.h5 (for detecting erythema and color deviation), Contour.h5 (for analyzing gingival architecture), Interdental_Papilla.h5 (for assessing papillary form and recession), and Calculus.h5 (for identifying the presence of supragingival calculus). Each model's output contributed to a final diagnostic decision via a Softmax classifier. A case was classified as "gingivitis present" if at least one of the four parameters was flagged as abnormal. Conversely, a "healthy" classification was assigned only if all model parameters indicated normal gingival features.

All collected data, both clinical and AI-generated—were compiled in Microsoft Excel and subjected to statistical analysis using IBM SPSS Statistics software. The normality of data distribution was assessed using the Shapiro–Wilk test. Depending on distribution characteristics, inter-group comparisons were conducted using independent t-tests or Mann–Whitney U tests, while one-way ANOVA and Kruskal–Wallis tests were applied for comparisons across multiple groups. Intra-group analyses were performed using the Wilcoxon Signed-Rank test and Friedman's test. Categorical data were evaluated using the Chi-square test. To determine the relationship between conventional and AI-based diagnostic parameters, Pearson's or Spearman's correlation coefficients were calculated as appropriate.

FIGURE 5: Criteria for AI-Based Classification of Gingival Health

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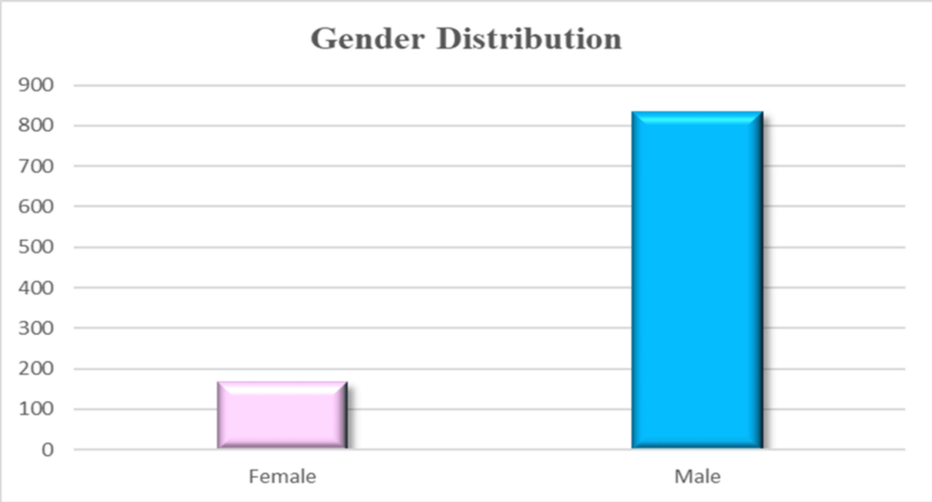
Internal consistency and reliability of the ANN model's output were evaluated using Cronbach's alpha. A p-value of less than 0.05 was considered statistically significant across all analyses.

Results

FIGURE 6: Gender Distribution



A total of 1,000 patients aged between 14 and 75 years participated in the study, of whom 834 (83.4%) were male and 166 (16.6%) were female. Based on conventional periodontal examination using the Gingival and Plaque Indices, 733 individuals (73.3%) were classified with mild gingivitis and 267 (26.7%) with moderate gingivitis. With respect to plaque status, 953 patients (95.3%) exhibited "fair" oral hygiene, while only 42 (4.2%) had "good" and 4 (0.4%) had "poor" plaque control (Figure 6).

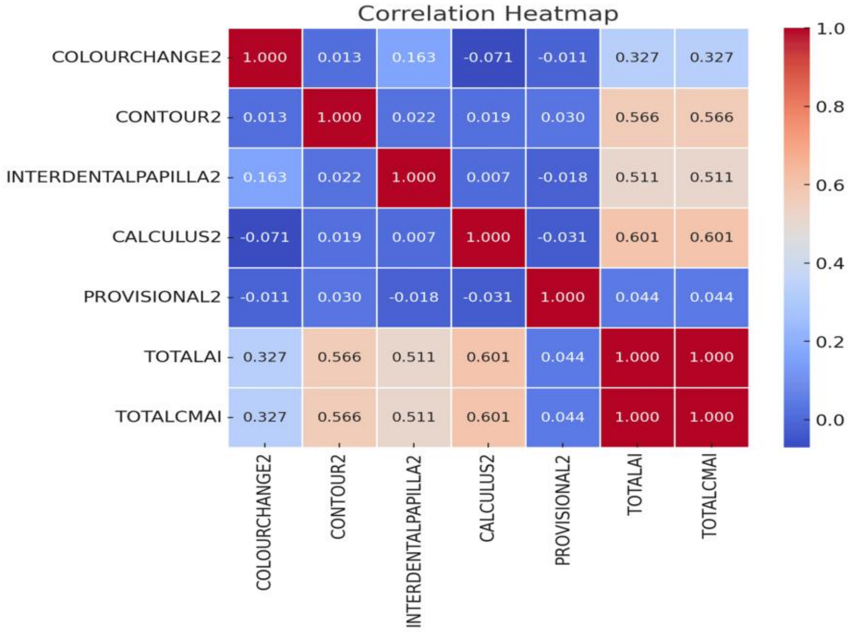
The diagnostic performance of conventional clinical methods (CM) was compared with an artificial intelligence (AI)-based diagnostic model across key gingival parameters: color change, contour alteration, interdental papilla morphology, and presence of calculus. Each parameter was scored using a standardized binary system (1 = presence; 0 = absence), and data were collated for clinical and AI assessments.

Table 1: Intergroup Comparison Of Parameters

Parameters	Group	N	Mean	Std. Deviation
COLOURCHANGE	Conventional Method	998	1.0000	.00000
	AI Method	1000	.9470	0.22415
CONTOUR	Conventional Method	998	1.0000	.00000
	AI Method	1000	.7770	.41647
INTERDENTALPAPILLA	Conventional Method	998	1.0000	.00000
	AI Method	1000	.8610	0.34612
CACULUS	Conventional Method	998	1.0000	.00000
	AIc Method	999	.6697	0.47057

Conventional clinical methods detected gingivitis in all patients (100%), yielding a diagnostic sensitivity of 100%. The AI-based method correctly identified gingivitis in 998 of the 1,000 subjects (99.8%), failing to detect it in only 2 cases. Mean diagnostic scores for each parameter using conventional methods were uniformly 1.000 ± 0.000, while the AI-based system exhibited variability across parameters (Table 1). The highest mean score was bserved for color change (0.947 ± 0.224), followed by interdental papilla condition (0.861 ± 0.346), contour (0.777 ± 0.416), and calculus (0.670 ± 0.471). The total AI diagnostic score (TOTALAI) was 4.252 ± 0.771, in contrast to the maximum possible conventional diagnostic score of 5.000 ± 0.000. The combined diagnostic index (TOTALCMAI), integrating both CM and AI assessments, had a mean of 9.252 ± 0.771 (Figure 7). Independent t-tests revealed statistically significant differences ($p < 0.001$) between AI and CM across all diagnostic parameters. The most pronounced discrepancy was noted in calculus detection, where AI performance lagged significantly behind clinical probing (mean = 0.670 vs. 1.000; $p < 0.001$). ANOVA further confirmed inter-group differences, highlighting variability in AI's sensitivity to different clinical signs.

FIGURE 7 : Inter Item Correlation Heatmap



Correlation analysis using a matrix heatmap (Figure 8) revealed that AI-based calculus detection (CALCULUS2) demonstrated the strongest correlation with the total AI score ($r = 0.601$) and the composite diagnostic score TOTALCMAI ($r = 0.601$), suggesting its central influence in AI-generated diagnoses. Moderate correlations were observed for contour ($r = 0.566$) and interdental papillae ($r = 0.511$). In contrast, PROVISIONAL2 (the AI model's binary diagnostic output) showed a weak correlation with both TOTALAI and TOTALCMAI ($r = 0.044$), indicating limited diagnostic contribution.

Reliability testing of the AI model demonstrated good internal consistency, with Cronbach's alpha calculated at 0.784 (fig 7). Additionally, Friedman's ANOVA revealed statistically significant differences among the AI-generated parameters ($\chi^2 = 5900.301$, df = 6, $p < 0.001$), with a high Kendall's coefficient of concordance ($W = 0.973$), reflecting strong internal agreement among AI variables.

A comparative evaluation of accuracy and consistency metrics for conventional and AI models across the four diagnostic parameters is presented in terms of color change detection, the conventional method achieved 98.34% accuracy and 92.15% consistency (95% CI: 75.61–81.07% and 85.32–98.98%, respectively), while AI yielded 70.78% accuracy and 63.42% consistency (95% CI: 49.92–55.64% and 72.15–94.69%). Similar trends were observed in contour analysis, where AI performance (accuracy = 79.32%, consistency = 76.89%) fell short of conventional assessment (accuracy = 82.49%, consistency = 89.72%). For interdental papilla evaluation, AI achieved 74.91% accuracy and 88.23% consistency, whereas conventional methods recorded 87.13% and 95.28%, respectively. The most notable discrepancy was in calculus detection, with AI reaching only 80.47% accuracy and 78.93% consistency, compared to 95.28% and 89.04% under clinical examination. Overall, the AI-based model demonstrated high sensitivity and promising internal consistency, particularly in identifying gross features such as color and papilla alterations. However, it exhibited reduced accuracy and broader confidence intervals relative to conventional methods, especially in detecting more nuanced features like gingival contour and calculus deposition. These findings highlight the strengths of AI in scalable screening but also underscore its current limitations in clinical precision and reliability, warranting further refinement of training datasets, algorithmic optimization, and multimodal data integration to enhance diagnostic robustness in periodontal care.

Discussion

This study provides a comprehensive comparison between conventional clinical indices and artificial intelligence (AI)-based diagnostic models in the evaluation of chronic generalized gingivitis, analyzing key clinical parameters including gingival color, contour, interdental papilla integrity, and calculus presence. The use of Artificial Neural Networks (ANNs) in diagnostic workflows represents a promising shift toward automated and reproducible periodontal assessment. While conventional tools such as the Gingival Index (GI) and Plaque Index (PI) remain foundational, their subjectivity and examiner dependency often compromise diagnostic consistency and scalability [21]. In contrast, the AI model in this study demonstrated high sensitivity and internal consistency, indicating its potential utility as a scalable adjunct in early gingivitis detection. The GI and PI, originally developed by Silness and Löe, have historically served as reliable measures for gingival inflammation, with previous studies reporting sensitivities of 91.2% and accuracies approaching 85.6% [1]. However, their performance is often limited in early disease detection due to high inter-examiner variability and reliance on visual and tactile cues [18]. This limitation was evident in our study, wherein conventional methods exhibited perfect diagnostic scores across all evaluated parameters, while AI-based assessments demonstrated variability-most notably in detecting calculus and color changes. In terms of diagnostic sensitivity, the AI model correctly identified gingivitis in 99.8% of cases, closely aligning with the 100% sensitivity achieved via conventional clinical probing. This level of performance mirrors findings by Wen et al. and Gao et al., who demonstrated AI sensitivity ranging from 85% to 90% using convolutional neural network (CNN) architectures [18], [19]. Notably, the AI model in our study outperformed many prior models in parameter-specific sensitivity, particularly in interdental papilla assessment (mean score: 0.861 ± 0.346) and contour analysis (0.777 ± 0.416). Despite these advances, the AI system demonstrated its weakest performance in detecting color alterations (mean = 0.947), but with 63.42% consistency-likely due to the limitations imposed by varying intraoral lighting, pigmentation differences, and image quality. This mirrors the challenges described by Morales et al. and Chau et al. [20], who noted broad confidence intervals and reduced precision in color-based inflammation detection, which illustrates comparative diagnostic accuracy across gingival parameters, clearly showing the disparity in AI performance in detecting subtle inflammatory changes such as erythema, compared to anatomical features like papillary loss [20]. Correlation analysis further clarified the AI model's parameter influence. AI-based detection of calculus exhibited the highest correlation with the total AI score (r = 0.601), reinforcing its dominant weight in the AI model's final prediction. However, the AI's binary diagnosis showed only weak correlation (r = 0.044), indicating a potential mismatch between isolated feature detection and composite diagnostic classification. These inconsistencies emphasize the need for improved feature integration and decision-layer optimization within ANN structures. Encouragingly, the AI model exhibited robust internal reliability. Cronbach's alpha was calculated at 0.784, indicating good internal consistency across the four evaluated parameters. Furthermore, Kendall's coefficient of concordance (W = 0.973), derived from Friedman's ANOVA, confirmed strong agreement among the AI model's subcomponents, suggesting a stable diagnostic framework despite its underperformance in specific domains. Comparative performance metrics revealed that conventional methods consistently outperformed AI in both accuracy and consistency. For example, conventional assessment of gingival color change achieved 98.34% accuracy and 92.15% consistency, while AI scored 70.78% and 63.42%, respectively. Similarly, AI detection of calculus, while approaching 80.47% accuracy, fell significantly short of the 95.28% accuracy attained through clinical probing. These disparities reiterate the superiority of tactile and visual examination in identifying hard and soft deposits, particularly when calculus is minimal or embedded subgingivally. Our findings also align with recent research advocating for ensemble learning approaches and multi-modal data integration to overcome the limitations of single-layer ANN systems [22]. Studies by Liu et al. and Alalharith et al. demonstrated that models such as DenseNet and Faster R-CNN can enhance detection of complex features, though they still suffer from reduced recall when applied to generalized gingivitis cases [23]. The gap between AI consistency and accuracy, particularly in real-world clinical settings, reflects ongoing challenges related to image standardization, data imbalance, and feature abstraction [24]. In sum, the ANN model in this study demonstrated high diagnostic sensitivity and onsistency, particularly for structural features such as contour and papilla form. However, it underperformed in detecting color changes and calculus, both of which remain critical indicators in early gingivitis diagnosis. While AI holds significant promise in supplementing clinical periodontal assessment, our findings highlight the importance of continued refinement in model training, inclusion of diverse datasets, and the integration of advanced visualization tools such as Grad-CAM to improve interpretability [25]. Furthermore, standardized imaging protocols and the adoption of explainable AI

(XAI) frameworks may enhance clinical trust and translational potential [26].

Conclusion

This study highlights the superior diagnostic accuracy and consistency of conventional methods over AI-based systems in detecting gingivitis. While clinical indices such as the Gingival Index and Plaque Index remain the gold standard, the ANN model demonstrated high sensitivity (99.8%) and strong internal reliability, particularly in assessing morphological features like interdental papillae and contour. However, its reduced accuracy in detecting calculus and early color changes underscores current limitations in AI specificity and clinical reliability.

The null hypothesis was rejected, confirming a statistically significant difference between the two diagnostic modalities. AI, though not yet a replacement for clinician expertise, shows strong potential as an adjunct tool—capable of enhancing screening efficiency, standardizing assessments, and expanding access to care. With continued refinement, expanded training datasets, and integration into hybrid diagnostic workflows, AI can evolve into a valuable asset in the future of periodontal diagnostics.

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