Original Article

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Dentistry Section

Diagnostic Performance Analysis using CBCT Assisted Artificial Intelligence for Detection of Supernumerary Teeth and Odontomes: A Retrospective Study

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ABSTRACT

Introduction: Artificial Intelligence (AI) is revolutionising dentistry by enhancing diagnostic precision, particularly for complex conditions like supernumerary teeth and odontomes. Accurate detection of these anomalies is essential for effective management and improved patient outcomes.

Aim: To evaluate the diagnostic performance of the machine learning models- Logistic Regression (LR), Random Forest (RF), and k-Nearest Neighbours (kNN), Gradient Boosting (GB), Artificial Neural Network (ANN), Stochastic Gradient Descent (SGD)- in detecting supernumerary teeth and odontomes using Cone Beam Computed Tomographies (CBCTs).

Materials and Methods: The present retrospective study analysed CBCT images of the maxillary and mandibular arches from patients who visited Saveetha Dental College and Hospital between February and September 2024 in Chennai, Tamil Nadu, India. A total of 240 high-resolution CBCT scans were included, categorised into three groups: supernumerary teeth (n=80), odontomes (n=80), and normal dentition (n=80), and patients exhibiting other dental anomalies were excluded. The dataset was divided into training (70%) and testing (30%) sets. Following preprocessing, multiple machine learning models- LR, RF, kNN, GB, ANN, and SGD- were employed for analysis using Orange data mining software.

Results: The present study evaluated the diagnostic performance of six machine learning models- LR, kNN, RF, ANN, SGD, and GB- for classifying CBCT images into supernumerary teeth, odontomes, and normal dentition. LR achieved the highest overall performance with an Area Under Curve (AUC) of 0.960, accuracy of 86.3%, and Mathews Correlation Coefficient (MCC) of 0.829, demonstrating strong generalisation across all classes. NN and GB also performed well, with comparable AUCs (0.960 and 0.944, respectively) and balanced classification metrics. RF showed good performance (AUC=0.951) but with a higher LogLoss, indicating less confident predictions. SGD and kNN underperformed, with kNN yielding the lowest accuracy (53.7%) and high misclassification rates. Confusion matrix analysis further supported these findings, highlighting LR, ANN, and RF as the most reliable models for distinguishing among the three diagnostic categories on CBCT images.

Conclusion: The LR proved to be the most effective model for detecting supernumerary teeth and odontomes. Future research should address dataset diversity and class imbalances while exploring ensemble modelling approaches to enhance diagnostic capabilities further.

Keywords: Abnormalities, Cone beam computed tomography, Computer reasoning, Machine learning models, Molars

INTRODUCTION

AI has revolutionised numerous fields, including healthcare and dentistry, by enabling faster, more precise and consistent diagnostic solutions [1]. Within dentistry, AI has emerged as a promising tool for managing complex dental anomalies, such as supernumerary teeth and odontomes. These conditions, though relatively rare, present significant clinical challenges due to their potential to cause complications such as delayed eruption, crowding, aesthetic concerns, and functional impairment [2].

Supernumerary teeth are extra teeth that develop in addition to the normal number of teeth, often disrupting dental alignment and complicating orthodontic treatment [3]. Odontomes, on the other hand, are benign odontogenic tumours comprising dental tissues like enamel, dentin, and pulp [4]. While odontomes are typically asymptomatic, they can hinder normal tooth development, leading to impaction or malocclusion. Accurate detection and classification of these anomalies are crucial for timely intervention and effective treatment planning. Traditional diagnostic methods primarily involve visual examination and interpretation of imaging modalities, such as Orthopantomograms (OPGs) and CBCT [5]. CBCT offers superior Three-dimensional (3D) imaging for detailed anatomical evaluation [6], its application in automated AI-based diagnostic studies few studies have harnessed the high potential of CBCT in conjunction with AI [7-9].

The present study addresses this gap by leveraging AI models to detect supernumerary teeth and odontomes, with a focus on optimising diagnostic workflows. By comparing the performance of various models, the research aimed to identify the most effective method for anomaly detection. This is particularly important as the field currently lacks substantial data on AI applications using CBCT images. The importance of the present study lies in its potential to improve diagnostic precision, reduce human error, and standardise anomaly detection processes. Additionally, integrating AI into routine dental diagnostics can reduce clinician workload, enhance decision-making, and improve patient outcomes [10]. By providing a systematic evaluation of machine learning models, this research contributes to the growing body of knowledge on AI applications in dentistry and highlights the need for future studies incorporating CBCT data to achieve greater diagnostic accuracy. Hence, the present study aimed to evaluate the diagnostic performance of the machine learning models like LR, RF, and kNN, GB, ANN, SGD in detecting supernumerary teeth and odontomes using CBCTs.

MATERIALS AND METHODS

The present retrospective study included 240 CBCT images which were retrospectively collected from patients who attended Saveetha Dental College between February 2024 and September 2024, Chennai, Tamil Nadu, India. The study received ethical approval from the Institutional Research and Ethical Committee, with clearance granted under the registration number IHEC/SDC/OMED-2205/24/265. This time-bound study included a total sample size of 240 CBCT scans, collected using a purposive sampling technique. The scans were equally divided into three groups: 80 scans exhibiting supernumerary teeth, 80 scans showing odontomes, and 80 scans with normal dentition. The methodology followed is more or less consistent with previous AI-based diagnostic studies in dental imaging and is supported by earlier research [11], where balanced datasets were effectively employed for training and evaluating machine learning algorithms in dental anomaly classification.

Inclusion and Exclusion criteria: Inclusion and exclusion criteria are given in [Table/Fig-1].

Inclusion criteria	Exclusion criteria
High-quality CBCT scans with sufficient resolution for diagnostic interpretation.	CBCT scans with motion artifacts or suboptimal image quality.
Radiographic evidence of either supernumerary teeth, odontomes, or normal dentition.	Syndromic patients or cases with systemic conditions influencing dentition and other dental anomalies.
No signs of syndromic or systemic conditions.	Incomplete imaging records or unclear diagnostic indicators.

[Table/Fig-1]: Inclusion and Exclusion criteria.

Study Procedure

The dataset was curated from institutional clinical records from February 2024 to September 2024 and included a variety of anatomical presentations to ensure generalisability. All analyses were performed using orange software [12] a visual programming and data mining platform suitable for classification, visualisation, and statistical analysis. Image embeddings were generated to convert the CBCT scans into numerical vectors usable by the machine learning models. To prepare the data for machine learning analysis, the following steps were undertaken: data processing was done by normalisation of pixel intensity values to a consistent scale and noise reduction was done to remove non-diagnostic artifacts and improve image clarity. Data splitting was done into two sets: 70% training and 30% testing, a ratio that ensures sufficient data for model learning while preserving an unbiased test set.

Image embeddings were generated using the Inception V3 architecture, a deep convolutional neural network developed by Google, known for its balance between accuracy and computational efficiency. Inception V3 is a 48-layer model that utilises advanced architectural concepts such as factorised convolutions, batch normalisation, and auxiliary classifiers to extract high-level, abstract features from input images. The model was used in a transfer learning framework, with weights pretrained on the ImageNet dataset, which comprises over 1.2 million natural images across 1,000 object categories. Although ImageNet consists of non-medical images, the lower and intermediate convolutional layers of Inception V3 capture universal visual patterns such as edges, textures, and spatial hierarchies that remain valuable in medical image analysis, including CBCT data. In this workflow, the final classification layers of the model were removed, and the output from the penultimate global average pooling layer was extracted as a fixed-length numerical feature vector (embedding) for each image. CBCT scans were first converted into Two-dimensional (2D) axial projections, resized to 299×299 pixels to comply with inception V3 input requirements, and normalised to a consistent pixel intensity range before being passed through the network. This embedding strategy enabled the translation of complex anatomical information into a structured, lower-dimensional feature space suitable for input into machine learning classifiers. Inception V3 was selected due to its robust performance in medical imaging tasks, proven generalisability with limited domain-specific data, and its computational efficiency, making it a suitable and effective feature extractor for classifying dental anomalies such as supernumerary teeth and odontomes in CBCT images [13].

Image embeddings were then fed into each of six supervised machine learning algorithms which were selected based on their widespread application and efficiency in classification tasks:

Logistic Regression (LR): A linear classifier valued for simplicity and effectiveness in binary and multiclass classification tasks [14].

Random Forest (RF): An ensemble learning method that builds multiple decision trees and aggregates their results for improved accuracy and robustness against overfitting [15].

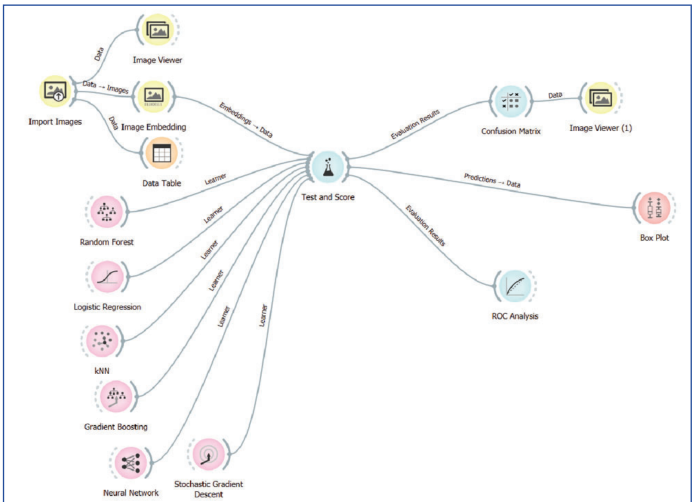
k-Nearest Neighbours (kNN): A non-parametric classifier that categorises instances based on proximity to labelled examples in the feature space [16].

Gradient Boosting (GB): An ensemble technique that builds models sequentially to minimise prediction error through gradient descent [17].

Artificial Neural Network (ANN): A deep learning model that mimics neural structures to learn complex, non-linear patterns [18].

Stochastic Gradient Descent (SGD): An optimisation algorithm that iteratively updates model parameters to minimise loss, especially effective for large-scale and sparse data [19].

Evaluation metrics was done to assess the diagnostic performance of each model, the following metrics were calculated: Accuracy, precision, recall, specificity, Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC), confusion matrices to visualise classification outcomes. The complete diagnostic workflow [Table/Fig-2] involved importing image datasets, inspecting them using the Image Viewer module, converting images into numerical embeddings, and passing them into the three AI models. Performance was evaluated using the Test and Score, Confusion Matrix, and ROC Analysis modules in orange software. Selected image results were also reviewed post classification for validation [11].



[Table/Fig-2]: The complete diagnostic workflow involved importing image datasets, inspecting them using the Image Viewer module, converting images into numerical embeddings, and passing them into the three AI models.

STATISTICAL ANALYSIS

The data was analysed using descriptive statistics and all model performance was analysed using Orange data mining software.

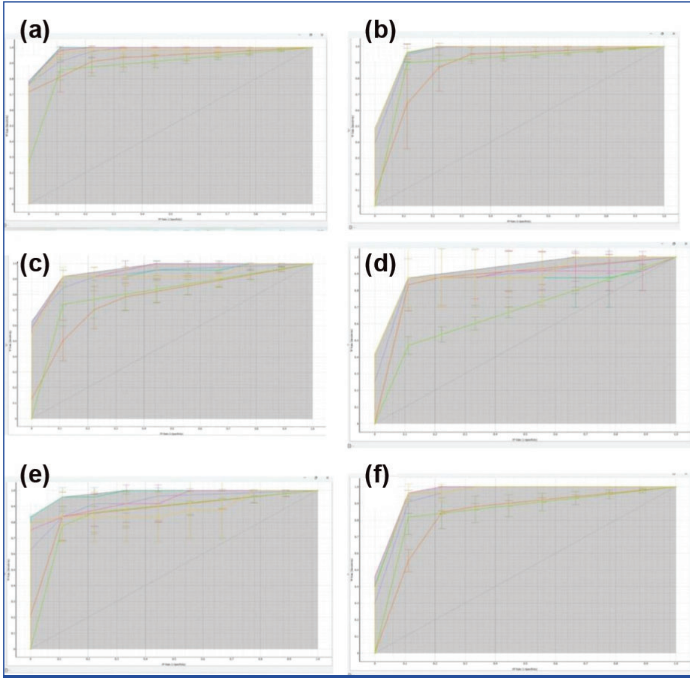
RESULTS

The diagnostic performance of six machine learning models- LR, kNN, RF, ANN, SGD, and GB- was evaluated using CBCT images categorised into three groups: supernumerary teeth, odontomes, and normal dentition. Evaluation metrics included AUC, Classification Accuracy (CA), F1 score, precision, recall, MCC, specificity, and logloss [11].

The data table consisting of accuracy, precision, recall, specificity, AUC for various machine learning models are shown in [Table/Fig-3] and the ROC are shown in [Table/Fig-4]. Among the six models, LR demonstrated the highest overall performance. It achieved an AUC of 0.960, indicating excellent discriminative ability between the three diagnostic classes. The accuracy of the model was 86.3%, and the F1 score was 0.859, reflecting a well-balanced trade-off between precision and recall. Precision and recall were recorded at 0.863 and 0.863, respectively, confirming the model's ability to minimise both false positives and false negatives. The MCC value of 0.829 showed strong correlation between the predicted and true classifications. Additionally, the specificity was 0.965, suggesting a low rate of false positives for the normal dentition class. The LogLoss of 0.584 indicated confident and well-calibrated predictions. The ANN performed comparatively well, also achieving an AUC of 0.960, with a slightly lower accuracy of 85.0%. The model's F1 score, precision, and recall were 0.847, 0.847, and 0.850, respectively, which are indicative of consistent and reliable predictions across all classes. The MCC for ANN was 0.814, further supporting its robust classification performance. The LogLoss, although slightly higher than LR at 0.895, was still within acceptable limits.

Models	AUC	CA	F1	Precision	Recall	MCC	Spec	LogLoss
Logistic Regression (LR)	0.960	0.863	0.859	0.863	0.863	0.829	0.965	0.584
k-Nearest Neighbours (kNN)	0.871	0.537	0.516	0.550	0.537	0.446	0.904	4.743
Random Forest (RF)	0.951	0.808	0.808	0.818	0.808	0.763	0.957	1.280
Neural Network (ANN)	0.960	0.850	0.847	0.847	0.850	0.814	0.965	0.895
Stochastic Gradient Descent (SGD)	0.870	0.787	0.789	0.808	0.787	0.741	0.959	7.659
Gradient Boosting (GB)	0.944	0.838	0.833	0.940	0.838	0.798	0.957	0.593

[Table/Fig-3]: Data table consisting of accuracy, precision, recall, specificity, AUC for various machine learning models.

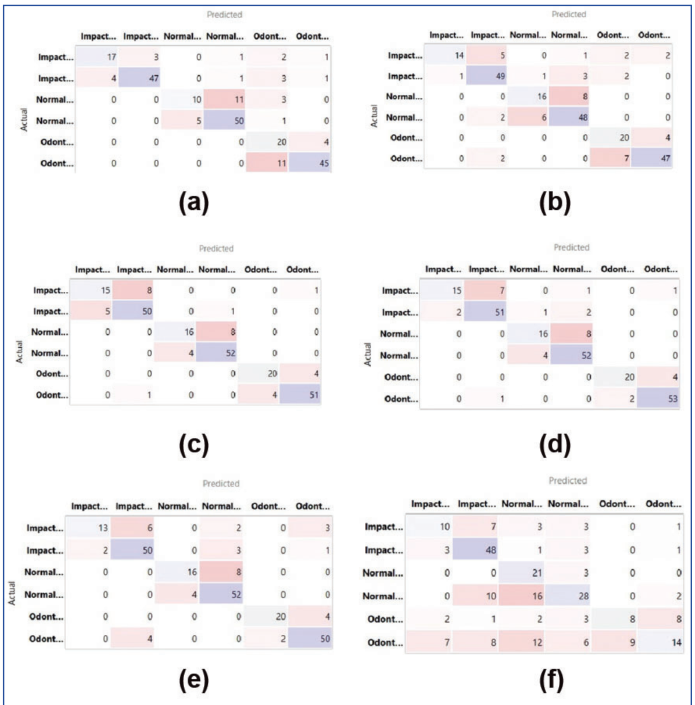


[Table/Fig-4]: The Receiver Operating Characteristic (ROC) curve of all the three groups of normal teeth, impacted supernumerary teeth and odontomes with showing differently the training and testing set of each group and their response to various machine learning models. (a) Training set of Impacted Supernumerary teeth group; (b) Training set of Normal dentition group; (c) Testing set of impacted supernumerary teeth group; (d) Testing set of normal dentition group; (e) Training set of Odontome group; (f) Testing set of Odontome group.

The GB also performed strongly, achieving an AUC of 0.944, and an accuracy of 83.8%. The F1 score (0.833), precision (0.940), and recall (0.838) reflected reliable classification. Its MCC value of 0.798 and a low LogLoss of 0.593 indicated good generalisation and confidence in predictions, comparable to the top two models. The RF model demonstrated good classification ability with an AUC of 0.951 and accuracy of 80.8%. The model yielded balanced F1 (0.808), precision (0.818), and recall (0.808) scores. The MCC of 0.763 was slightly lower than that of the top three models, and the LogLoss of 1.280 suggested relatively lower confidence in prediction probabilities, though the model remained robust in its performance.

In contrast, SGD displayed moderate classification performance. While the model achieved an AUC of 0.870 and accuracy of 78.7%, the F1 score (0.789), precision (0.808), and recall (0.787) were slightly below those of the other models. Its MCC value of 0.741 was acceptable, but a very high LogLoss of 7.659 indicated poor calibration, with predictions likely being overconfident or inconsistent. Lastly, the kNN model showed the lowest performance across all metrics. With an AUC of 0.871 and accuracy of only 53.7%, it failed to classify the CBCT images effectively. The F1 score (0.516), precision (0.550), and recall (0.537) were low, suggesting poor balance and a high number of misclassifications. The MCC value was 0.446, and the LogLoss was notably high at 4.743, confirming the model's poor confidence and overall unsuitability for this diagnostic task.

The confusion matrix analysis, as shown in [Table/Fig-5], revealed notable differences in classification performance across the six models. LR demonstrated the most consistent and accurate predictions, correctly classifying all impacted (supernumerary) cases and misclassifying only a few normal and odontome cases, indicating strong generalisation across all classes. Similarly, RF and ANN models achieved high precision, correctly identifying nearly all impacted and odontome cases, with minor confusion between



[Table/Fig-5]: The confusion matrix analysis revealed notable differences in classification performance across the six models: (a) Stochastic Gradient Descent (SGD); (b) Random Forest (RF); (c) Neural network; (d) Logistic Regression (LR); (e) Gradient boosting (GB); (f) k-Nearest Neighbours (kNN).

normal and odontome categories. GB also performed well but showed a slightly higher degree of misclassification, particularly between odontome and normal classes. SGD exhibited moderate performance, with a noticeable tendency to misclassify normal as odontome and vice versa, while also producing a few errors in identifying impacted cases. In contrast, the kNN model demonstrated the weakest performance, with significant confusion across all three categories, especially misclassifying odontome as normal and normal as impacted. These results align with the quantitative metrics and further underscore the superior classification capability of LR, RF, and ANN models, particularly in distinguishing impacted and odontome cases from normal dentition on CBCT images.

DISCUSSION

The advent of AI in dentistry has revolutionised diagnostic capabilities, particularly for complex dental anomalies such as supernumerary teeth and odontomes [20]. These rare conditions can significantly impact a patient's oral health by causing crowding, delayed eruption, or functional impairments. Traditional diagnostic methods, though widely used, often rely heavily on clinician expertise and can be time consuming and prone to variability [21]. AI-based diagnostic tools, including machine learning algorithms and deep learning models, have demonstrated remarkable accuracy in identifying and classifying these anomalies on radiographs and 3D imaging modalities [22]. By leveraging large datasets, AI systems can detect subtle patterns and correlations that may elude even experienced clinicians, thereby enhancing diagnostic precision and consistency [2]. As the integration of AI continues to evolve, it holds the potential to transform patient care by offering a more personalised, accurate, and streamlined approach to managing dental anomalies [8].

These findings underscore the potential of LR as a reliable diagnostic tool for dental anomalies, particularly when applied to structured and preprocessed imaging datasets which is in accordance with Ciftci BT et al., in 2024 [23]. The study highlights the importance of data preprocessing and balanced dataset representation in enhancing the performance of AI models which is in accordance with Okazaki S et al., in 2022 [11]. Although RF and kNN models exhibited moderate and low performance, respectively, their limitations provide critical insights into the challenges of applying AI to dentistry, such as data imbalance and model sensitivity. Future research should explore the use of larger, more diverse datasets and ensemble modelling techniques to combine the strengths of multiple models, thereby improving diagnostic accuracy and clinical applicability. The present study demonstrates that AI-driven models, particularly LR, have the potential to standardise and streamline the detection of supernumerary teeth and odontomes reducing reliance on subjective interpretation and improving patient outcomes. By addressing the identified limitations, such as the underrepresentation of odontomes in the dataset, and leveraging the strengths of advanced AI methodologies, dental practitioners can achieve more accurate, efficient, and consistent diagnostic outcomes in clinical practice.

In summary, the results underscore the utility of machine learning models, especially LR, ANN, and GB, in supporting diagnostic workflows for detecting supernumerary teeth and odontomes in CBCT scans. These models offer promising avenues to reduce diagnostic subjectivity, enhance early detection, and standardise clinical evaluations in dental practice. Further research involving larger datasets, multicentre validation, and integration with clinical decision support systems is warranted to fully harness the potential of AI in dental diagnostics.

Limitation(s)

While the findings of the present study are promising, a few limitations must be acknowledged. The dataset was limited to 240 CBCT scans from a single institution and it is a time bound study, which may not fully represent the variability in anatomical and pathological presentations seen in broader populations. Additionally, although image embeddings were used effectively for training traditional machine learning models, this approach may not fully capture the spatial complexity inherent in volumetric CBCT data. Another limitation is the restriction of diagnostic categories to three classes- supernumerary teeth, odontomes, and normal dentition which may not account for more subtle, overlapping, or rare anomalies encountered in clinical practice. Moreover, model explainability was not explored in the present study, which is an important factor for clinical acceptance and trust in AI systems. Future research should focus on using larger, multicentre datasets and incorporate raw CBCT volumes into end-to-end deep learning pipelines such as 3D convolutional neural networks. Including more diverse diagnostic categories and explainable AI tools would enhance clinical applicability. Integration of these models into clinical decision support systems could eventually facilitate real-time, automated diagnostics and improve patient care in dental radiology.

CONCLUSION(S)

This study demonstrated the effectiveness of various machine learning models in the classification of CBCT images for the diagnosis of supernumerary teeth, odontomes, and normal dentition. Among the models tested, LR showed the highest overall performance, offering excellent accuracy, predictive reliability, and calibration. ANN and GB also exhibited strong diagnostic capabilities, reinforcing the potential of both conventional and ensemble learning approaches in medical image analysis. In contrast, kNN and SGD were less effective, highlighting the importance of model selection based on data characteristics. The findings underscore the value of integrating AI-driven tools into dental diagnostics, particularly for conditions requiring detailed imaging interpretation such as odontogenic anomalies. Leveraging machine learning in CBCT analysis can support clinicians in achieving faster, more accurate diagnoses, ultimately enhancing patient care. Future studies with larger datasets and end-to-end deep learning frameworks are recommended to further validate and expand upon these results, paving the way for real-time, AI-assisted diagnostic systems in routine dental practice.

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- Manual Googling: Aug 07, 2025
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