

A Random Forest-based Automatic Classification of Dental Types and Pathologies using Panoramic Radiography Images

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Detection and classification of tooth types and anomalies is crucial for accurate dental assessment, treatment planning, and overall oral health preservation. The integration of machine learning expedites the classification of tooth types and anomalies with lesser manual intervention, streamlining the diagnostic process and enhancing overall efficiency in dental healthcare. This study addresses the automated classification of oral types and anomalies in panoramic radiograph images which is a challenging task due to the complexity and variability of oral conditions. We propose an innovative approach using hyperparameter-optimized Random Forest ensemble learning achieved through Genetic Algorithm. Various pre-processing techniques are applied to enhance data quality by removing null values and minimizing noise in image data followed by feature extraction. The model consists of 10 Decision Trees trained on various subsets, with hyperparameters systematically optimized using a Genetic Algorithm. Outcomes from individual Decision Trees are aggregated through majority voting. Comprehensive experimental assessment, including an 80-5-15 training-validation-testing split, results in an impressive 98% accuracy. This highlights the effectiveness and superiority of our approach and demonstrates the potential of Random Forest ensemble learning for automated accurate classification, with the added benefit of Genetic Algorithm-driven hyperparameter tuning for improved model performance. Our approach may be applied in real-time for telemedicine and can help dental professionals make decisions about prevention, diagnosis, and treatment planning.

Keywords: Decision tree, Dental diagnosis, Feature extraction, Image pre-processing, Oral classification

Introduction

Many remarkable benefits can be had from having good oral health. Our physical attractiveness, cerebral inspiration, and sense of fulfillment have all improved. It makes sense to provide the best dental healthcare possible. Medical imaging technologies and Artificial Intelligence may aid in faster diagnostics and improved dental treatment planning.¹ Machine Learning (ML), a subset of Artificial Intelligence (AI), has significantly advanced medical image processing by enabling computers to learn from experience.^{2,3} AI and ML have significantly enhanced dental treatments as well, with their extensive potential in dentistry being researched. Machine learning models, trained on labeled data, utilize various classification methods to predict outcomes based on category labels.^{4,5} Decision Tree (DT) and Random Forest (RF) are two of the ML classification models. Azar *et al.* employ decision tree classification, a method that divides data into smaller components to construct interconnected decision

nodes and leaf nodes, determining classifications based on dataset features and selecting attributes using Attribute Selective Measures.⁶

Decision tree classification has been applied in different fields of research, including medical and non-medical areas.^{7,8} Random forest, a scalable and user-friendly machine learning technique, often yields impressive results, suitable for both classification and regression tasks. Its ensemble approach, combining multiple classifiers with decision trees as base models where the final classification is determined through majority voting, distinguishes it from single decision trees, enhancing its effectiveness as a robust classifier.^{9,10} Denisko *et al.* employ a bootstrap technique to partition the training dataset into multiple subsets for Random Forest training, effectively minimizing overfitting and accuracy biases by majority voting and reducing variance by leveraging multiple data samples.¹¹ The ensemble random forest has demonstrated superior accuracy in various research domains, suggesting its potential applicability in dentistry for improved outcomes.

In dentistry's evolving landscape, accurate classification of teeth and anomalies like impacted

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and cap teeth in panoramic radiographs, also known as Orthopantomogram (OPG) X-rays, poses a significant challenge due to the intricate patterns within dental structures. This study proposes an ensemble Random Forest enhanced with a genetic algorithm to address this challenge. The work shows potential for improving diagnostic precision and streamlining treatment planning, thereby enhancing patient outcomes and clinical workflow efficiency. Random Forest offers superior performance due to its ability to handle large datasets with high dimensionality, while mitigating overfitting through ensemble averaging of multiple decision trees, thereby enhancing generalization and robustness in classification. The different tooth types and anomalies, namely cap and impacted teeth samples, considered in our work are given in Fig. 1. Incisors are sharp-edged teeth for cutting, canines are pointed teeth for tearing, premolars have flat surfaces for grinding, and molars are large, multi-cusped teeth for crushing and grinding food. Impacted teeth occur when a tooth fails to emerge fully through the gum. A dental crown or cap, is a tooth-shaped cap that is placed over a damaged or decayed tooth to restore its shape, size, strength, and appearance.

Literature Survey

Numerous studies have been conducted to examine the segmentation and classification of dental image analysis. Zakirov *et al.* used deep neural networks for Cone-Beam Computed Tomography (CBCT) images, achieving 96.3% accuracy in locating teeth and an average of 0.94 AUROC for detecting common tooth conditions.¹² Güven *et al.* developed an automated method for segmenting teeth in panoramic dental X-rays using the CatBoost algorithm, incorporating center point identification, feature set creation, and employing k-fold cross-validation alongside grid search optimization to mitigate overfitting, evaluated through learning curves and multiple performance metrics.¹³

Okazaki *et al.* conducted a feasibility study on the use of AlexNet-based deep learning models for classifying dental anomalies in panoramic

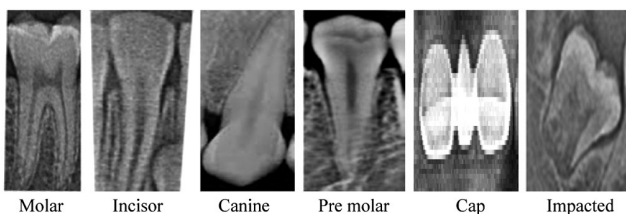


Fig. 1 — Tooth types and anomalies samples

radiographs across 150 images, achieving accuracies of 70%, precision of 70.8%, sensitivity of 70%, and an F1 score of 69.7% in categories including no anomalies, single supernumerary teeth, and odontomas.¹⁴ A deep learning strategy Employing Convolutional Neural Networks (CNNs), specifically Faster R-CNN for teeth detection and VGG-16 for numbering in panoramic radiographs, was introduced by Tuzoff *et al.*, leveraging a large dataset and demonstrating performance comparable to expert radiologists in evaluation, highlighting deep learning's promise in dental radiograph analysis to improve diagnostic efficiency and accuracy.¹⁵

Muresan *et al.* proposed a systematic approach for analyzing dental images that includes data preprocessing, tooth detection, and classification through semantic segmentation with the ERFNet model, enhanced by semantic image annotations across 14 classes for diverse dental conditions, and employs 1D convolutions for residual functions, presenting an exhaustive analysis of results including accuracy (89%), precision (98%), and recall (91%), alongside comparisons to other methods, demonstrating both high performance and computational efficiency.¹⁶

Zhang *et al.* addressed data scarcity in teeth recognition and classification across 32 locations by employing a cascading web topology with a manually created label tree, leading to a compartmentalized approach involving three distinct CNNs—VGG16 for NET1, ensemble learning for NET2, and candidate filtering for NET3—each tackling a specific subtask to simplify task complexity and employing strategies like weighted precision logic refinement for NET1, and ensemble learning techniques for NET2 and MOD4, enhancing classification efficiency.¹⁷

Miki *et al.* developed an automated system using deep CNNs for identifying and classifying teeth in cone beam CT images through two multisided CNN models, focusing solely on teeth detection, and achieving an accuracy rate of 91.0%.¹⁸ Laishram *et al.* utilized the Faster R-CNN deep neural network architecture to detect and classify two types of teeth and five dental irregularities in orthopantomogram radiography images (OPG), achieving detection and classification accuracies of 90% and 99% respectively.¹⁹ Laishram *et al.* also proposed another method for the recognition and classification of dental types and irregularities. The dropout method has been used to improve network classification performance and lessen overfitting.²⁰ Additionally Laishram *et al.*

proposed a CNN-based method with dropout regularization to classify two types of teeth and two different defects, training the fully connected layer of the CNN through hybrid GA-BP learning.²¹

Karaoglu *et al.* evaluated the effectiveness of Mask R-CNN and a heuristic algorithm-based numbering approach for panoramic dental radiographs following the FDI system, employing k-fold cross-validation ($k = 5$) to assess the dataset, and introducing a three-step heuristic algorithm to improve segmentation and numbering outcomes, achieving mean average precision (mAP) at IOU of 0.5, precision, recall, and f1 scores of 92.49%, 96.08%, 95.65%, and 95.87% respectively.²²

Our study proposes a novel method to classify different tooth types, namely incisors, molars, premolars, canines, and anomalies, including caps and impacted teeth in panoramic radiographs, using Random Forest with bagging. It addresses the limitations of existing techniques, such as dataset size constraints, imbalances, and computational demands, and offers an advanced approach combining Genetic Algorithms for optimization and ensemble learning with Random Forest for classification.

Proposed Methodology

Our study is a comprehensive approach to identifying certain dental pathologies from raw radiographs by performing several image pre-

processing steps on dental panoramic radiographs using ensemble forest techniques. The block diagram of our algorithm is shown in Fig. 2. The steps involved in our methodology are as follows:

1. Acquiring Images
2. Pre-processing of the Images
3. Construction of the RF model
4. Training of the RF model
5. Testing and Prediction of Classes
6. Training and Testing

Acquiring Images

The acquired image is not processed and needs to be preprocessed as per the requirements of the work. Our study utilizes Orthopantomograms (OPG), commonly known as panoramic X-rays, which offer a comprehensive 2D view of dental structures, upper and lower jaws, and surrounding tissues in a single image. These OPG images were sourced from the Cosmo Dental Clinic, Manipur and captured using the CS8100 Dental OPG machine with dimensions not exceeding 250 KB and a resolution set at 720×1280 . Once the image is acquired, other processing techniques are applied to process the image. A panoramic X-ray is given below in Fig. 3.

Pre-processing of the Images

The purpose of pre-processing is to enhance the image data, remove unnecessary distortions, or

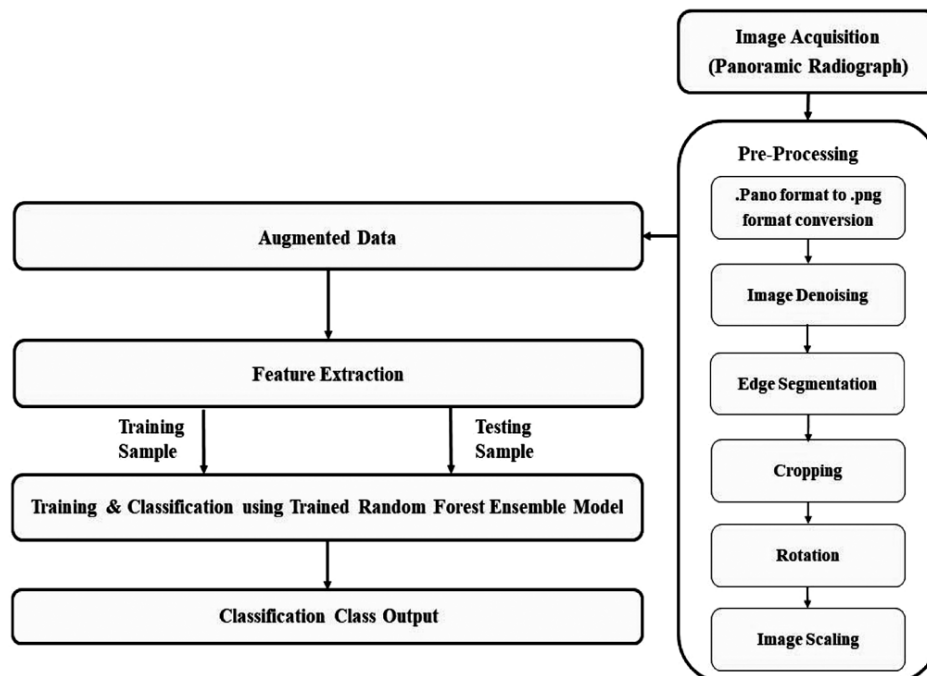


Fig. 2 — Block diagram of the proposed algorithm



Fig. 3 — A Panoramic X-ray

enhance certain features of the image that are important for further processing.^{23,24} Raw data in .pano format is converted to .png before further processing using any pre-processing techniques. The steps involved in the pre-processing techniques are listed below:

1. Image Denoising
2. Edge Segmentation
3. Image Cropping
4. Image Rotation
5. Image Scaling

Image Denoising

In medical image analysis, denoising is a crucial preprocessing step aimed at accurately restoring the original image from noisy inputs while retaining vital features like edges and textures. In our study, OPG image denoising is achieved through the application of a median filter.

Edge Detection

Edge detection is also vital in medical image processing, traditionally relying on derivatives of the image intensity function for conventional edge detection, which offer high performance speeds but struggle with complex medical images or those with acquisition artefacts. In our proposed study, we have employed active contour for segmenting an image based on its boundaries.²⁵

Image Cropping

Image cropping is the most common pre-processing technique. It is utilized to define the Region of Interest (ROI) and eliminate any obtrusive or unneeded information from Panoramic Radiography images, which helps to increase accuracy while accelerating processing and reducing the chance of error.

Image Rotation

The images are rotated around their centers to a predetermined angle of 45° or 90° to improve the

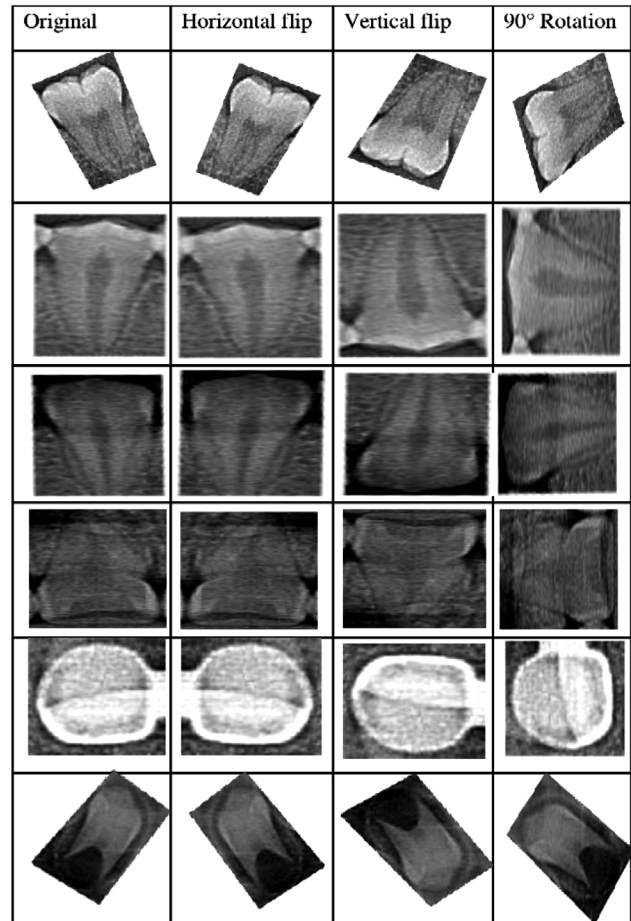


Fig. 4 — Image Augmentation: (a) Molar, (b) Pre-Molar, (c) Canine, (d) Incisor, (e) Cap, and (f) Impacted

viewing of the acquired images. This is carried out to preserve consistency in how images are represented.

Image Scaling

The process of representing and resizing original images by using a larger and lower number of pixels is known as image scaling. Scaling is advantageous for many machine learning and image processing applications. It helps to reduce the number of pixels in the image. It can reduce the time required to train the neural network.

Image Augmentation

Data augmentation creates new data from the original data using various operations like horizontal or vertical flip, and rotation. It increases the overall number of datasets, thereby having a bigger dataset. The sample results of increasing data are shown for the six classes in the order of molar, pre-molar, canine, incisor, cap, and impacted in Fig. 4.

Feature Extraction

In dental image analysis, extracting geometric features plays a crucial role in accurate teeth classification. Following pre-processing and augmentation, our emphasis lies in employing bounding boxes to enclose individual teeth in dental images. These bounding boxes are defined by coordinates, denoted as x_{min}, y_{min} for the top-left corner and x_{max}, y_{max} for the bottom-right corner. These coordinates serve as fundamental features, capturing the spatial position and extent of each tooth.

In addition to bounding box coordinates, we compute the area and perimeter of each bounding box to further characterize the teeth as shown in Table 1. The area, calculated as the product of the width and height, provides a quantitative measure of the tooth's spatial coverage. The perimeter, representing the total length of the bounding box boundary, contributes insights into the tooth's overall shape. The area (A) is calculated as the product of the width and height of the bounding box.

$$A = (x_{max} - x_{min}) \times (y_{max} - y_{min}) \quad \dots (1)$$

The perimeter (P) is calculated as the sum of all four sides of the bounding box.

$$p = 2 \times (x_{max} - x_{min} + y_{max} - y_{min}) \quad \dots (2)$$

This comprehensive array of geometric features, including bounding box coordinates, area, and perimeter, has been intricately crafted to lay a robust groundwork for teeth classification in dental image analysis. Using these geometric features, input patterns are created as shown in Table 1 and these patterns are fed as input data to the Random Forest model for training and testing.

Construction of the RF Model

Random Forest employs an ensemble of decision trees for classification, mitigating overfitting risks by

training each tree on a dataset subset. A Random Forest classifier is proposed for automatically identifying tooth types, including incisors, molars, pre-molars, canines, and dental anomalies, in panoramic x-rays. It dynamically adjusts its forest size to improve classification accuracy, showing promising outcomes on benchmark datasets.²⁶ A diagram of the Random Forest classification is shown in Fig. 5.⁽¹⁰⁾ The random forest algorithm has two steps. Firstly, construct the random forest and compute it in the constructed random forest classifier.²⁶ The Random Forest algorithm works as follows:

1. Randomly select K data points.
2. DT will be created for each selected sample, and the result will be predicted for every decision tree.
3. A majority vote will then be taken on each prediction.
4. The algorithm will select the prediction with the most votes as the final prediction

The best attributes of nodes are selected based on **Attribute Selection Measures (ASM)** and we used Information Gain for the ASM.

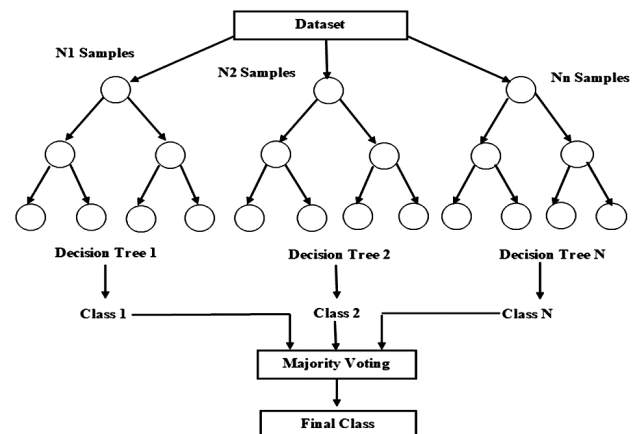


Fig. 5 — Random forest classification

Table 1 — 12 Input patterns

Sl. No.	Class	Bounding Box Coordinates				Area	Perimeter
		X_{min}	Y_{min}	X_{max}	Y_{max}		
1	000	154	192	195	238	1886	216
2	000	432	279	469	347	2520	218
3	001	412	279	438	345	1716	184
4	001	424	218	449	270	1300	154
5	010	289	275	312	350	1725	196
6	010	374	272	398	357	1968	212
7	011	367	204	391	266	1488	172
8	011	354	274	378	343	1656	186
9	101	472	151	514	203	2184	188
10	101	120	236	169	282	2303	192
11	100	395	268	423	319	1428	158
12	100	417	264	448	320	1736	174

Information Gain

Information Gain is used to split the node and build decision trees. The change in entropy after dividing a data set based on attributes is measured as information gain. It determines how much information the attribute provides about the class. Using the information gain value, DTs are created by splitting the nodes. According to the algorithm, the node with the highest information gain will be split first. It can be calculated using the formula below:

$$\text{Information gain} = E(Y) - E(Y/X) \quad \dots (3)$$

where, $E(Y)$ and $E(Y/X)$ indicates entropy before and after the split respectively.

Entropy is the randomness or uncertainty measure of the data $[X]$. The entropy E can be calculated using the equation:

$$E = - \sum_{i=1}^N p_c \log_2 p_c \quad \dots (4)$$

where, p_c indicates the Probability of randomly selecting a sample in class c and N represents the total number of classes.

Training and Testing

In our work, we employed a dataset comprising 3000 images distributed across 6 distinct classes for training. Additionally, 180 images were specifically set for validation, while the testing phase involved the utilization of 1600 randomly selected samples. This methodical approach aimed to improve our model's efficacy and robustness.

Hyperparameter Tuning using GA

Some hyperparameters are tuned or optimized using the Genetic Algorithm to get the optimal performance of the model. The details of the hyperparameters are as follows:

1. *n_estimators*: The *n_estimators* parameter specifies the number of trees in the forest of the model.
2. *max_depth*: The *max_depth* parameter specifies the maximum depth of each tree.
3. *min_samples_split*: The *min_samples_split* parameter specifies the minimum number of samples required to split an internal leaf node.

A Genetic Algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems.

The basic steps in GA are:

1. Initialization
 - a) In the beginning, the GA randomly creates a population of complete bit strings (solutions). For

our application, the population contains 50 strings/solutions. The solution represents the hyperparameters to be optimized. The number of trees is represented by an 8-bit substring binary string, maximum depth of each tree by a 6-bit binary substring and the minimum number of samples required splitting a node by a 4-bit substring. The total number of bits in each string/solution is 18 bit.

- b) Give the definition of the fitness.

2. Evaluation

- a) For each of the three substring, i.e., *n_estimators*, *max_depth* and *min_samples_split*, we convert them into numeric values. These values are passed to the system for use during training and validation/testing. Finally, we find the fitness/accuracy of each solution (bit string).

3. Selection

- a) Choose a set of bit string whose accuracy/fitness value is greater than some specific number.

4. Reproduction

- a) The population is modified using three operators namely selection, crossover and mutation.
- b) This process (Evaluation, Selection, and Reproduction) is repeated for many generations and we choose a set of bit string whose fitness value is greater than some specific number.

The integration of GA ensures that the model operates at its peak efficiency, extracting optimal performance from the underlying Random Forest classifier by finding the optimal values of the hyperparameters.

Results and Discussion

Class Representation

In our work, the classification of dental images involves six specific classes: molar, pre-molar, canine, incisor, cap, and impacted. To enhance the decision-making process within decision trees, a binary representation has been meticulously assigned to each class, as comprehensively detailed in Table 2. This systematic binary encoding serves as the

Table 2 — Class and Its Binary Representation

Binary Representation	Class
000	Molar
001	Pre-Molar
010	Canine
011	Incisor
100	Cap
101	Impacted

foundational framework for the subsequent development of the ensemble model.

Dataset

The Cosmo Dental Clinic, Manipur, India contributed the dataset for this research, which included Panoramic radiographs taken with a CS8100 Dental OPG machine. As shown in Table 3, 3000 images of 6 classes are used for training, 180 images for validation and 1600 random samples for testing.

Bootstrap Aggregation or Bagging

The training methodology in this study encompasses the utilization of bagging, characterized by random sampling with replacement. This systematic approach involves partitioning the dataset for the concurrent training of 10 decision trees.

The basic steps are as follows:

1. Define the size of the sample.
2. Choose a data point randomly for a sample.
3. Retain it in the main set after selection (replacement).
4. Choose a data point once more from the primary training set for the sample and then hold it back after selection.
5. Continue with steps 1 through 4 until you have reached the desired sample size.

This technique aims to enhance the robustness and generalization of the ensemble model.

GA Optimization for Hyperparameter Tuning

A comprehensive overview of the Genetic Algorithm (GA) optimization employed for hyperparameter tuning over diverse generations is

given in Table 4. The binary strings within the table signify the optimal configurations for key parameters, including `n_estimators`, `max_depth`, and `min_samples_split`. In Table 4, the first row shows the details at 10th generation. 00001111 011001 0100 is the binary string at 10th generation which gives the highest fitness/accuracy. The first substring gives a numeric value of 15 which is the `n_estimators`, the second substring gives a value of 25 which is `max_depth` and the last substring gives a value of 4 which is for `min_samples_split`.

The last row shows the details at 450th generation. 00001010 011110 0010 is the binary string at 450th generation which gives the highest fitness/accuracy of 98%. The first substring gives a numeric value of 10 which is the `n_estimators`, the second substring gives a value of 30 which is `max_depth` and the last substring gives a value of 2 which is for `min_samples_split`. The table shows the highest fitness/accuracy values, highlighting the effectiveness of the genetic algorithm in fine-tuning the model. This optimization process greatly improves the model's performance and precision, aligning with the goals of advanced hyperparameter tuning methods in machine learning.

Training

In our study, we employ a robust ensemble model classifier constructed through the integration of 10 Decision Trees. This strategic ensemble approach significantly augments the overall robustness and predictive capabilities of the model, thereby fortifying its efficacy in handling complex data patterns and improving overall performance.

Table 3 — Dataset Samples

Training Set	Validation Set	Test Set
500 Molar class images	30 Molar class images	1600 random images
500 Pre-Molar class images	30 Pre-Molar class images	
500 Canine class images	30 Canine class images	
500 Incisor class images	30 Incisor class images	
500 Cap class images	30 Cap class images	
500 Impacted class images	30 Impacted class images	

Table 4 — GA optimization

Generations	<code>n_estimators</code>	<code>max_depth</code>	<code>min_samples_split</code>	Highest Fitness/Accuracy
10	15	25	4	90
50	25	52	7	85
100	07	30	5	88
150	22	52	3	87
200	36	30	6	82
250	12	45	5	86
300	65	35	4	89
350	27	32	8	92
400	19	15	5	94
450	10	30	2	98

Entropy

The entropy curves of DT1 and DT2 are shown in Figs 6(a) and 6(b). The proportion of data points belonging to the positive class, $p(+)$ represents the x-axis and the y-axis measures their respective entropies.

OOB error

The computation of the Out-Of-Bag (OOB) error is pivotal for evaluating Random Forest classifier performance. This metric is computed from samples excluded from individual tree training, referred to as out-of-bag samples. It provides a reliable measure of the model's capacity to generalize to unseen data, offering valuable insights into its overall performance. Averaging the OOB errors from each tree produces a comprehensive OOB error for the entire Random Forest. This aggregated error measurement encapsulates the ensemble's overall performance and its adaptability to diverse datasets. The graphical representation of the OOB error, as shown in Fig. 7, contributes to a detailed understanding of how the Random Forest Classifier performs across various scenarios and data subsets, providing a visual

representation of its effectiveness and reliability for real-world applications.

ROC Curve

The Receiver Operating Characteristic (ROC) curve, illustrating the relationship between the true positive rate and the false positive rate, is meticulously plotted at various threshold levels, as shown in Fig. 8. The x-axis signifies the false positive rate, while the y-axis represents the true positive rate. Through meticulous analysis of the ROC curve, we determined the Area Under the Curve (AUC) to be 98%. This high AUC value serves as a robust indicator of the model's precision in accurately predicting dental types and anomalies. The

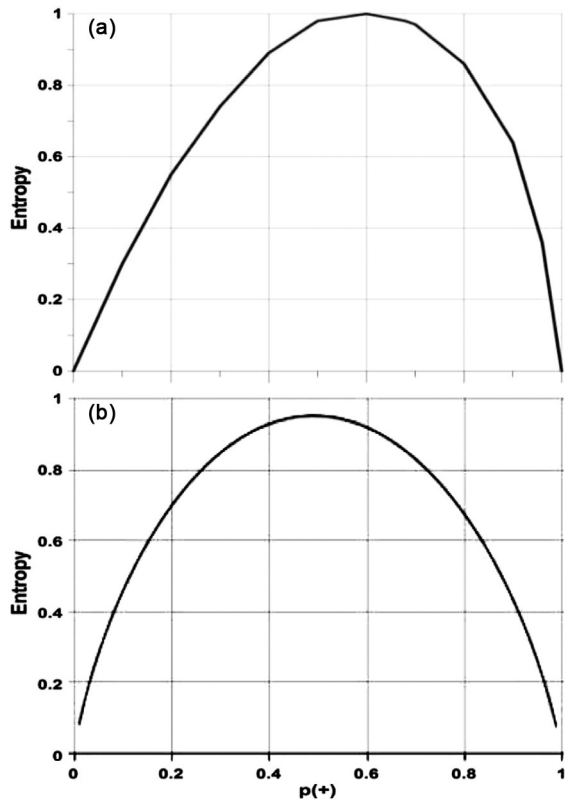


Fig. 6 — (a) Entropy for Decision Tree 1 (DT1), and (b) Entropy for Decision Tree 2 (DT2)

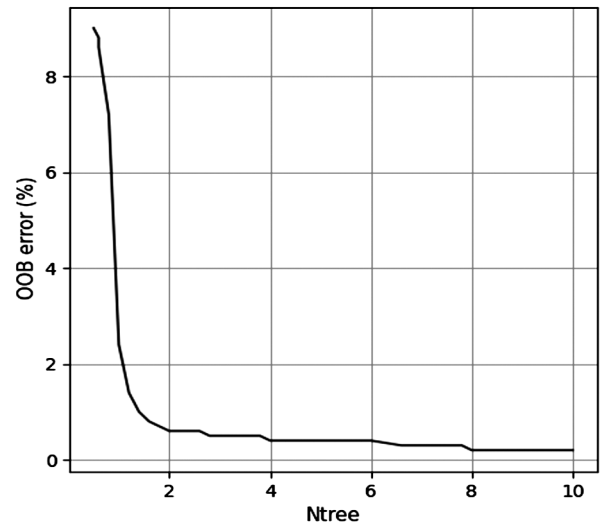


Fig. 7 — OOB error

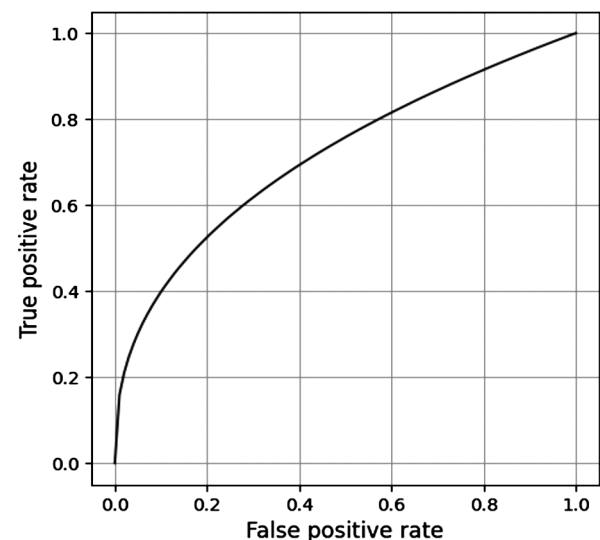


Fig. 8 — ROC Curve

comprehensive ROC analysis provides valuable insights into the classifier's discriminatory capabilities and its effectiveness across different classification thresholds, reaffirming its reliability in real-world dental image classification scenarios.

Testing

The evaluation of the test sample input involves a meticulous examination across ten decision trees, with the resulting outcomes meticulously documented in Table 5. A comprehensive analysis of specific test instances, such as Test No. 1 and Test No. 2, unveils the individual predictions rendered by each decision tree.

For testing No. 1,

1. The prediction given by Decision Trees DT2, DT3, DT4, DT7 and DT10 is Pre-Molar (001).
2. The prediction given by Decision Trees DT1, DT6, DT8 and DT9 is Canine (010).
3. The prediction given by Decision Tree DT5 is Molar (000).

The ultimate classification, determined through the ensemble model after the voting process, consolidates these diverse predictions, resulting in the final categorization as Pre-Molar (001).

For testing No. 2,

1. The prediction given by Decision Trees DT2, DT4, DT5, DT6, DT9 and DT10 is Canine (010).
2. The prediction given by Decision Trees DT1, DT3 and DT7 is Pre-Molar (001).
3. The prediction given by Decision Tree DT8 is Molar (101)

The ensemble model, utilizing a voting mechanism, determines the final prediction as Canine (010). This comprehensive testing method, encompassing multiple decision trees and subsequent integration into the ensemble model, highlights the model's effectiveness in handling diverse dental image classifications. These evaluations play a crucial role

in understanding the robustness and precision of the ensemble model in real-world scenarios of dental image classification.

Performance Measurements

In our comprehensive evaluation of classification methods, we explore the details of four essential performance metrics: precision, recall, F1-score, and accuracy. These metrics offer a detailed understanding of the model's effectiveness in distinguishing between various dental image classes. The equations of the metrics are given below:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad \dots (5)$$

$$\text{Recall} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \quad \dots (6)$$

$$\text{F1 score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \dots (7)$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{False Negative} + \text{True Negative}} \quad \dots (8)$$

False positive represent instances where the model incorrectly predicts a positive outcome, true positive are correct positive predictions, true negative are accurate negative predictions, and false negative indicate instances where the model incorrectly predicts a negative outcome. The false positive rate is the proportion of actual negatives incorrectly classified as positives, while the true positive rate is the proportion of actual positives correctly identified by the model.

To measure the performance of our work, we used four parameters namely Precision, Recall, F1 Score, and Accuracy and the values are shown in Table 6. We calculate the values of Precision, Recall, F1 Score, and Accuracy of the six classes and the averages come out to be **96%**, **96%**, **95%** and **98%** respectively.

The Confusion Matrix for the classification is shown in Fig. 9. The method has been implemented

Table 5 — Testing Results of 10 Samples

Testing No.	Prediction of Decision Trees										Voting
	DT1	DT2	DT3	DT4	DT5	DT6	DT7	DT8	DT9	DT10	
1	010	001	001	001	000	010	001	010	010	001	001
2	001	010	001	010	010	010	001	101	010	010	010
3	000	000	000	001	000	000	001	010	000	000	000
4	101	010	010	010	101	001	010	101	010	010	010
5	101	000	001	001	000	000	101	000	000	000	000
6	010	101	010	010	101	101	010	101	101	101	101
7	100	101	100	100	100	101	101	011	100	100	100
8	000	000	001	000	001	001	001	001	001	000	001
9	101	010	010	101	010	101	101	010	101	101	101
10	011	101	101	011	011	101	011	101	011	011	011

Table 6 — Precision, Recall, F1 Score and Accuracy

Teeth Classes	Precision	Recall	F1 Score	Accuracy (%)
Molar	0.98	0.94	0.95	0.98
Pre Molar	0.96	0.95	0.95	0.99
Canine	0.99	0.99	0.98	0.99
Incisors	0.96	0.98	0.94	0.98
Cap	0.95	0.96	0.93	0.99
Impacted	0.93	0.95	0.94	0.98
Average	0.96	0.96	0.95	0.98

Molar	302	0	0	0	0	12
Pre Molar	0	180	0	9	0	0
Canine	0	6	488	0	0	4
Incisors	0	0	4	236	0	0
Cap	6	0	0	0	167	0
Impacted	0	0	0	0	8	178

Fig. 9 — Confusion Matrix

with ten decision trees and majority voting using random forest.

According to the matrix:

- i. Based on the actual 314 molar samples, our system predicted that 302 are molars and 12 are Impacted.
- ii. Based on the actual 189 pre-molar samples, our system predicted that 180 are pre-molar and 09 are Incisors.
- iii. Based on the actual 498 Canine samples, our system predicted that 488 are Canine, 6 are pre-molar, and 4 are Impacted.
- iv. Based on the 240 Incisor samples, our system predicted that 236 are Incisor and 4 are Canine.
- v. Based on the actual 173 Cap samples, our system predicted that 167 are Cap and 06 are Molars.
- vi. Based on the actual 186 Impacted samples, our system predicted that 178 are Impacted and 08 are capped.

Discussion

The comparison of our proposed work with other standard algorithms is shown in Table 7. Muresan *et al.* use the ERFNet neural network model and a Histogram-based segmentation algorithm. The method detects Dental anomalies with 89% accuracy. The model may struggle with unusual or infrequent

dental conditions.¹⁶ In another work, Ekert *et al.* use the CNN model for the detection of Apical Lesions (ALs) and the method detects them with 87% accuracy.²⁷ The method proposed by Krois *et al.* uses a CNNs for Periodontal Bone Loss detection. The method obtains an accuracy of 81%.²⁸ Singh *et al.* developed a model that deploys Deep CNN for oral type classification and obtains an accuracy of 95%. The method is prone to noise in CT images, affecting accuracy, especially in the presence of unclear imaging.²⁹ Vinayahalingam *et al.* comes up with a technique using a Convolutional Neural Network (MobileNet V2) for the recognition of Tooth anomalies in the third molar and obtains an 87% accuracy of detection.³⁰

Muramatsu *et al.* proposed a model using CNN for the classification of Dental Tooth Types and Dental Conditions which gives an accuracy of 93.2% and 98.0% respectively.³¹ The method proposed by Celik *et al.* uses YOLOv3 for the classification of molar-impacted teeth and obtains a classification accuracy of 96%. It has challenges in detecting small pathologies; the model may struggle with subtle or small dental pathologies.³² Park *et al.* developed a technique using Masked R-CNN and Faster R-CNN that obtains 92.14% accuracy detection and a mean Average Precision (mAP) of 59.09%.³³

AL-Ghamdi *et al.* proposed a method that deploys a Neural Search Architecture Network (NASNet) which classifies dental anomalies namely Cavity, filling and implant with an accuracy of 96%.³⁴ The method proposed by Duman *et al.* deploys a CNN for Taurodontism tooth classification that provides a sensitivity of 0.8650, precision of 0.7898 and F1-score of 0.8257.⁽³⁵⁾

Our proposed method uses a series of pre-processing steps to enhance the quality of image data and remove unnecessary distortions or noises and also enhances certain features of the image that are important for further processing. We also employ a Genetic Algorithm to tune or optimise hyperparameters to get the optimal performance of the model. Using Random Forest with ensemble learning for classification tasks on the panoramic radiographs helps to avoid overfitting and thereby improves system performance and accuracy.

For our work, the proposed model gives a classification accuracy of 98% which is better than other state of the art algorithms. As Random Forest contains a high number of decision trees, the method

Table 7 — Comparison of our proposed method with other standard method

Authors	Year	Model	Modality/ X-ray	Dataset Size and training error	Teeth Types/ Anomalies	Classification Accuracy
Muresanet <i>et al.</i> ¹⁶	2020	ERFNet neural network model and Histogram-based segmentation algorithm	OPG	2000 & 0.24	Tooth types and Anomalies	89%
Zhang <i>et al.</i> ¹⁷	2020	CNN	OPG	Limited & 0.15	Tooth Types	precision and recall of 95.8% and 96.1% respectively
Miki <i>et al.</i> ¹⁸	2018	Deep CNN	CT	52 CT volumes & 0.09	Tooth Types	91%
Anuradha <i>et al.</i> ²¹	2020	CNN with Dropout	OPG	1800 & 0.05	Tooth types and Anomalies	97.92%
Ekhert <i>et al.</i> ²⁷	2019	CNN	OPG	2001 & 0.04	Tooth Anomalies	87%
Krois <i>et al.</i> ²⁸	2019	CNN	OPG	2001 & 0.07	Tooth Anomalies	81%
Singh <i>et al.</i> ²⁹	2020	CNN	OPG	12000 & 0.03	Tooth types	95.6%
Vinayahalingam <i>et al.</i> ³⁰	2021	CNN (MobileNet V2)	OPG	500 & 0.13	Tooth Anomalies	87%
Muramatsun <i>et al.</i> ³¹	2021	CNN	OPG	950 & 0.06	Tooth Anomalies	93.2% and 98.0%
Celik <i>et al.</i> ³²	2022	YOLO v3	OPG	440 & 0.04	Tooth Anomalies	96%
Park <i>et al.</i> ³³	2022	Masked R-CNN and Faster R-CNN	OPG	455 & 0.12	Tooth Anomalies	92.14% mean Average Precision (mAP) 59.09%
Abdullah <i>et al.</i> ³⁴	2022	Neural Search Architecture Network (NASNet)	OPG	116 & 0.08	Tooth Anomalies	96%
Duman <i>et al.</i> ³⁵	2022	CNN	OPG	434 & 0.05	Tooth Anomalies	Sensitivity, precision, and F1-score of 0.8650, 0.7898, and 0.8257, respectively.
Our proposed system	2023	Random Forest with Hyperparameter-GA	OPG	4780 & 0.03	Tooth types and Anomalies	98%

is highly accurate and robust. Random forest takes the results from each decision tree and makes a majority voting on all the results. The random forest does not depend only on a single decision tree result. By taking the average of every prediction, it balances out biases and avoids overfitting.

Conclusions

A new method for the classification of dental types and anomalies has been developed in this paper. The method uses a Random Forest consisting of ten decision trees and performs ensemble learning. The OPG image is used as input data and it has been pre-processed to improve the image data that suppresses unwilling distortions and enhances some image features important for further processing. Features are extracted from the preprocessed image and input patterns are created to use as input to the decision trees. Using the concept of random sampling with a replacement called bagging, the dataset is divided for training the 10 decision trees. To split the node and build decision trees, we used Information Gain using the concept of entropy. The model is trained and tested and performance measures are compared with

various state-of-the-art methods. It has been found that our proposed method performs better than other works, with a recall of 96%, precision of 96%, F-1 score of 95%, and accuracy of **98%**.

This work can be improved by including more oral anomalies and using different radiography images. Increasing the number of tuned hyperparameters will also enhance system performance. In the future, more advanced machine learning methods with explainable AI can be explored. The proposed approach can be used in real-time for telemedicine and to blend different types of data. It can also be explored to make the model easier to understand and address imbalances in the data. These steps will improve the automatic detection of oral issues and make healthcare decisions more accurate. To further enhance performance, other ensemble learning approaches can be explored using different neural networks as base models and a meta model.

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Conflict of Interest

The authors have no conflict of interest to declare.

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