

“Machine Learning Model to Assess the External Apical Root Resorption from the CBCT image”

*2023 Orthodontic Faculty Development
Fellowships (OFDFA)*

Dr Divakar Karanth

DKaranth@dental.ufl.edu
O: 415-988-2969

FollowUp Form

Award Information

In an attempt to make things a little easier for the reviewer who will read this report, please consider these two questions before this is sent for review:

- Is this an example of your very best work, in that it provides sufficient explanation and justification, and is something otherwise worthy of publication? (We do publish the Final Report on our website, so this does need to be complete and polished.)*
- Does this Final Report provide the level of detail, etc. that you would expect, if you were the reviewer?*

Title of Project*

“Machine Learning Model to Assess the External Apical Root Resorption from the CBCT image”

Award Type

Orthodontic Faculty Development Fellowship Award (OFDFA)

Period of AAOF Support

July 1, 2023 through June 30, 2024

Institution

University of Florida Board of Trustees

Names of principal advisor(s) / mentor(s), co-investigator(s) and consultant(s)

Dr. Calogero Dolce,

Amount of Funding

\$30,000.00

Abstract

(add specific directions for each type here)

Attached

Respond to the following questions:

Detailed results and inferences:*

If the work has been published, please attach a pdf of manuscript below by clicking "Upload a file".

OR

Use the text box below to describe in detail the results of your study. The intent is to share the knowledge you have generated with the AAOF and orthodontic community specifically and other who may benefit from your study. Table, Figures, Statistical Analysis, and interpretation of results should also be attached by clicking "Upload a file".

Developing a machine learning (ML) tool to identify and classify the severity of resorption from segmented CBCT images.pdf

Were the original, specific aims of the proposal realized?*

This research aimed to develop an artificial intelligence algorithm that will help the clinician diagnose and quantify the amount and severity of the root volume loss from the cone beam CT scan. This will be an alternative to a clinician's subjective visual examination and interpretation. This can help the orthodontists to make an early diagnosis of External Apical Root Resorption from the progress radiographs and pause the orthodontic treatment on time to prevent further resorption. However, to our knowledge, no research has been done regarding the automated diagnosis of root resorption in orthodontic patients.

- Yes we achieved our goals. We established the norm for tooth volume for the entire dentition through the newly developed automated tooth volume assessment tool from the CBCT image. We also successfully developed and tested the tool to calculate tooth volume loss during treatment. We have developed a user-friendly interface for clinicians to input the data and get the results instantly without knowing about the program's backend. We also developed a machine learning algorithm to classify the root resorption based on the Root/Crown Ratio. This machine learning algorithm can classify root resorption as moderate and severe and distinguish it from normal roots with an accuracy of 92%. This machine learning model demonstrated promising performance in accurately calculating R/C values and classifying them into predefined categories. Evaluation metrics such as accuracy, precision, recall, and F1-score indicated robust performance across different classification tasks. The high performance of the model suggests its potential utility as a reliable tool for assisting dental practitioners in R/C assessment.

Cases with Normal Roots Without Resorption: The high final precision indicated that when the model predicts a tooth as having normal roots, it is correct 92% of the time. The recall signifies that the model successfully identifies 96% of all normal cases. The F1-score, balancing precision and recall, suggests the model is highly reliable in identifying normal cases. The support is the number of normal instances in the test dataset.

Moderate Root Resorption: The precision indicates that the model correctly identifies moderate root resorption cases 86% of the time. Recall of the model shows that it identifies 76% of the actual moderate cases, indicating some cases might be missed or misclassified. The F1-score here points to a moderate level of accuracy and reliability for these cases, and the support is 17 cases of moderate root resorption in the test dataset.

Severe Root Resorption: The model shows perfect precision and recall, identifying every severe case correctly. The perfect F1-score indicated exceptional model performance in this category. Note that the support of 7 being a smaller sample size may impact the reliability of the 100% scores.

Overall Model Performance: Accuracy indicates that the model correctly classifies 92% of the cases across all categories. Macro Average Precision of 93% reflects the average precision across all categories, indicating a high level of overall precision. Macro Average Recall of 90% across all categories is also high, demonstrating the model's effectiveness in identifying true cases. A high overall F1 score of 91% suggests a balanced model performance between precision and recall. Figure 2 is a Graphical representation of the dispersion of the data in the third pass.

In collaboration with the College of Education and the Digital Worlds Institute at the UF College of the Arts, I have developed Virtual Reality (VR) software designed to teach orthodontic biomechanics. Utilizing funding from the AAOF grant, I hired a skilled VR game developer to contribute to this project. Development was carried out using Blender and Unity, with the Meta Quest 3 headset deployed to provide an immersive learning experience. We have completed the first module, which features 12 highly immersive scenarios, marking the first resource of its kind in orthodontics. This VR platform offers interactive modules for a comprehensive understanding of orthodontic biomechanics.

Were the results published?*

No

Have the results of this proposal been presented?*

Yes

To what extent have you used, or how do you intend to use, AAOF funding to further your career?*

James A. McNamara Orthodontic Faculty Fellowship Award has four components:

Research domain:

The research project is developing an artificial intelligence program to measure root volume and compare the pre-treatment and post-treatment to determine root volume loss during orthodontic treatment. We have successfully developed a program to calculate the tooth volume from the segmented CBCT called "QuantRoot." Now, we have the average volume for all the teeth, and the program can compare the tooth volume of a given case to the average volume.

Educational Skills Development

Subscription to AAO's CE Passport Doctor, AAO online access to the conference, and CE course content have been phenomenal. I could look up any topic of interest at any time and learn from the leaders in the field. Through the support of the AAOF grant, I have attended several conferences. With the support of AAOF funding, it was possible to devote time to writing an extensive review on "The applications of digital technology in postgraduate orthodontic education," which was published in the Seminars in Orthodontics. I have attended several conferences, which enhanced my knowledge.

Teaching Skills Development

We have successfully developed a virtual reality program to demonstrate biomechanics and 3D images segmented from a CBCT for diagnosis and treatment planning. I hired a game developer to work on developing a virtual reality program. I have been accepted to attend the ITL Course "Institute for Teaching & Learning Program" in August 2024. This elaborate course of four days greatly enhanced my teaching skills.

Clinical Skills Development

Attending meetings such as the AAO annual meeting, SAO meeting, Angle meeting, ADEA meeting, and the Moyers Symposium has helped me tremendously to improve my clinical skills. I have attended all the above conferences during 2023-25.

Accounting: Were there any leftover funds?

\$0.00

Not Published

Are there plans to publish? If not, why not?*

Research results are to be published. Currently working on 2 manuscripts on root resorption.

One review article has been published, and the grant has been acknowledged.

Karant, D., Abu Arqub, S. H., & Dolce, C. (2024). The applications of digital technology in postgraduate orthodontic education. *Seminars in Orthodontics*, 30(4), 436-442.

<https://doi.org/10.1053/J.SODO.2024.03.003>

VR Orthodontic Biomechanics Software Development:

Divakar S Karant, Anjali Soni(g), J Kang(&), and Calogero Dolce(&). Revolutionizing Orthodontic Education, Diagnosis and Treatment Planning Using Virtual and Augmented Reality Technologies. Office of Research College of Dentistry Spring Synergy Research Day. Volume 1: Abstract 7. 2024.

https://research.dental.ufl.edu/wordpress/files/2024/03/2024-Spring-Synergy-ResearchDay-Program_Final.pdf

Presented

Please list titles, author or co-authors of these presentation/s, year and locations:*

1. Karant, D. (2025 April 25-27) External Root Resorption: Detection and quantification using Machine Learning. E poster Presentation at the American Association of Orthodontists (AAO) 2025 Annual Session in Philadelphia, PA.

2. Karant, D. (2025, March 12-15) Machine Learning Model to Assess the External Apical Root Resorption from the CBCT image, Accepted Oral presentation at the 2025 AADOCR/CADR Annual Meeting & Exhibition. New York City, New York, USA. But could not attend due to family health issues.

3. Karant, D. (2024, March 01-01). Detection and quantification of external root resorption using Machine Learning. 48th Annual International Conference on Craniofacial Research, Ann Arbor, Michigan.

<https://moyerssymposium.org/>

4. Karant, D. (2024, June 06-06). Orthodontic Research: Unraveling the Science behind the Smiles. Half a day CE course. Khammam, India.

5. Karant, D. (2024, June 07-07). Artificial Intelligence-driven Orthodontics for Enhanced Patient Care. One-day CE course. Bangalore, India.

6. Karant, D. (2024, June 08-08). Orthodontic Research. Half a day CE course. Bangalore, India.

7. Soni, A. Karant, D. (2024, March 29-29). Revolutionizing Orthodontic Education, Diagnosis and Treatment Planning Using Virtual and Augmented Reality Technologies. Spring Synergy Research Day, UF College of Dentistry. University of Florida College of Dentistry, College of Dentistry.

<https://research.dental.ufl.edu/resources/spring-synergy/>

Was AAOF support acknowledged?

If so, please describe:

One review article has been published, and the grant has been acknowledged.

Karant D, Arqub SA, Dolce C. The applications of digital technology in postgraduate orthodontic education. In Seminars in Orthodontics 2024 Apr 3. WB Saunders.

<https://www.sciencedirect.com/science/article/pii/S1073874624000409>

All the above presentations had a slide on acknowledging the AAOF Support:

Funding: This research is supported by the James A. McNamara Orthodontic Faculty Fellowship Award, American Association of Orthodontists Foundation Grant ID #: AGR DTD 06-19-2023.

Internal Review

Reviewer comments

Reviewer Status*

File Attachment Summary

Applicant File Uploads

- Developing a machine learning (ML) tool to identify and classify the severity of resorption from segmented CBCT images.pdf

Developing a machine learning (ML) tool to identify and classify the severity of resorption from segmented CBCT images

Divakar Karanth*

Clinical Associate Professor & Residency Program Director

Department of Orthodontics

University of Florida

DKaranth@dental.ufl.edu

Samatha Montoya

Aiosa and Hoffman Orthodontics,

1530 Business Center Drive, Suite 2

Fleming Island, FL 32003

Calogero Dolce

Professor and Chair

Department of Orthodontics

University of Florida

cdolce@dental.ufl.edu

Mateus G Rocha

Clinical Associate Professor &

Director, Center for Dental Biomaterials

University of Florida

mrocha@dental.ufl.edu

* Corresponding author

Divakar Karanth

1395 Center Drive,

UF College of Dentistry / Department of Orthodontics

P.O. Box 100444, Gainesville, FL 32610-0444

DKaranth@dental.ufl.edu

Abstract:**Objectives:**

Current methods for identifying and classifying root resorption from radiographs have been very subjective. Our goal was to create a novel, efficient, and reliable method for identifying and quantifying orthodontically induced root resorption volumetrically. This research aimed to (1) develop a program to calculate tooth volumes and establish normal volumes for each tooth, (2) create a program to calculate root volume loss from orthodontic treatment by comparing pre-treatment and post-treatment tooth volumes, (3) to develop a program to calculate the volume of the crown and the root separately, establishing a norm for the root crown ratio (R/C) for each tooth and (4) develop a machine learning (ML) tool to identify and classify the severity of resorption from segmented Cone beam computed tomography (CBCT) images.

Methods:

CBCTs of orthodontic patients from the University of Florida's orthodontic department were utilized for this study. They were obtained with the i-CAT 3D Dental Imaging System at 0.3mm resolution. Teeth were segmented using Diagnostics software, which automates the process. From 1,182 segmented images of orthodontic patients' CBCTs, 127 were selected for this pilot study. The roots and crowns were segmented manually using Meshmixer. An ML machine learning program for identifying and classifying root resorption was written in Python 3.8. The dataset was split 70% for training, 20% for testing, and 10% for validation. Future testing will be used as a separate dataset from another university. Ethical guidelines were followed, ensuring confidentiality and anonymity, with IRB approval from the University of Florida.

Results:

A program was developed that calculates the crown and root volume separately. This study established a norm for tooth's root crown ratio (R/C). An ML tool using a random forest classifier was developed, which shows that an R/C ratio ≤ 80.81 indicates severe resorption with high certainty, while an R/C ratio > 101.84 indicates normal roots with high certainty. Intermediate nodes indicate moderate resorption with varying certainty.

Conclusions:

This project initiated the development and validation of an ML-based application for automated R/C calculation and classification in dental imaging. The ML model shows significant potential as a diagnostic aid for root resorption severity classification. Continued refinement and validation are recommended to maximize its utility and reliability. Before integrating this technology into clinical workflows, further research is needed to address limitations and unlock its full potential. Leveraging advanced ML techniques enhances the efficiency and accuracy of dental diagnosis and treatment planning, improving patient care.

Introduction:

Diagnosis and treatment planning in the orthodontic specialty rely heavily on the patient's available records and technological advances to analyze those records. Specifically, diagnosing and quantifying external apical root resorption is determined solely based on the patient's radiographs, since there is no other way to see the teeth unless you explant and examine them physically. Most studies find that there is some amount of apical root resorption in teeth during and after orthodontic treatment has been completed¹⁻⁶. A review of root resorption in relation to orthodontics looked at the causes of root resorption and the radiological techniques used in orthodontics to quantify root resorption. The review suggests that a panoramic radiograph is not as diagnostic in the anterior region of the mouth because of patient positioning and a narrow focal trough⁷. This makes a case for better imaging modalities in orthodontics since panoramic and cephalometric radiographs are standard for the specialty. Another project is warranted to use or develop a more sophisticated imaging system for visualizing and quantifying external apical root resorption before, during, and after orthodontic treatment. This paper will continue to expand upon external apical root resorption and orthodontically induced inflammatory root resorption, dental radiology and cone beam computed tomography, artificial intelligence and machine learning, segmentation of radiographs, and how they are interrelated.

External Root Resorption

A systematic evaluation of root resorption in patients with orthodontic tooth movement compared with randomized control trials of patients with fixed appliances only. Literature revealed that root resorption is unaffected by archwire sequence or bracket prescription, and that previous trauma or tooth morphology are contributing factors. The results were inconclusive but suggest orthodontists should use light forces to intrude incisors⁶. Most of the available literature concludes that the most severely and frequently affected teeth by external apical root resorption are the incisors^{1,2,8-11}. Despite the frequency and severity of root resorption noted in incisors, there is some mention of significant amounts of root resorption in first molars as well⁸.

In one study, continuous light and heavy forces were put on premolars, then tooth movement and root resorption were monitored for 4 or 7 weeks. There was no difference in movement when the force was doubled, but surprisingly, the root resorption was greater in the teeth with the lighter force⁵. This, and many other studies, mention that individual variations greatly affect the amount of root resorption and reparative potential observed^{4,5,12}. It is important that clinicians move teeth with the optimal force to be most efficient with treatment time while considering the bone and soft tissue responses. Clinicians must balance the efficiency of movement with the probability of orthodontic induced inflammatory root resorption⁵. While correlating the severity of apical root resorption after orthodontic treatment and the effects of the duration of treatment, root resorption was detected on a panoramic radiograph in all groups of teeth studied. Increased duration of treatment increases the risk of apical root resorption².

Root resorption can be classified depending on the type of stimulation: infection, pressure, or ankylosis. Certainly, continuous pressure recruits the resorptive cells to the area of the root that is most likely to have shortening effects. Results show "radiographically, orthodontic pressure resorption is located in the apical third of the root, and no signs of radiolucency can be observed in the bone or the root"³. As we are seeing radiographically, there are no signs of infection in the bone

or tooth, it is inferred that the root resorption is being attributed to the orthodontic tooth movement. After further review, there is contradicting information based on study design, models and appliances used, direction of force, and movement through spongy versus cortical bone. Some studies state that there is a direct correlation between force and movement, and others state there is no significant correlation⁵. Interestingly, evaluating apical root resorption of canines after standardized orthodontic retraction illustrated that the resorption of canines was not clinically significant¹³.

It is widely accepted that orthodontic tooth movement uses the inflammatory process as an integral part of the treatment protocols and the clinician should be aware of the risks involved⁴. A risk prediction model was used to observe multiple different factors that could affect external apical root resorption. It showed that the external apical root resorption was influenced most by gender, duration of treatment, a Hyrax appliance, initial anterior open bite, and initial premolar extraction¹. Alternatively, duration, magnitude, and type of force were studied, and it was found that there is not necessarily a correlation between root resorption and tooth movement in general. It also contradicts a previously mentioned study by concluding that there is root resorption with continuous forces, not more so when compared to interrupted forces. Root resorption was recorded with type and magnitude, but was not significantly affected by them; however, duration was highly associated with root resorption. As weekly assessments were completed, there was more root resorption each time¹².

Dental Radiography and Cone Beam Computed Tomography (CBCT)

The advent of newer technologies has led to better, more accurate, and efficient treatment planning in the field of orthodontics. All dental specialties use digital imaging in some way for diagnosis, treatment planning, and follow-up, and so it is important for clinicians to know the limitations of each¹⁴. In recent years, we have seen increased use of cone beam computed tomography and digital scanning to aid in planning biomechanics and predicting treatment outcomes. With conventional two-dimensional radiographs, it is difficult to have a proper diagnosis as the jaws and dentition are developing in three planes and can involve both the skull and soft tissue of the face. The clinician is forced to infer a 3-dimensional diagnosis from a static 2-dimensional image. This can result in a misdiagnosis because it is not an accurate representation of the patient's craniofacial complex¹⁵.

CBCT generates 3D data at lower radiation doses than conventional CT¹⁶. CBCT has transformed maxillofacial imaging with its extensive applications across the fields of dentistry, ranging from diagnosis, patient care, to treatment planning. With this comes certain steps to reach an accurate and efficient outcome. It is important to take care to eliminate errors in each step for better diagnosis and segmentation. Some errors include field of view and voxel size, which influence the image quality and, in turn, the digital treatment planning¹⁴. A project using 2-dimensional imaging to explore root resorption found that quantitative results of radiographs are inaccurate because of magnification errors and low reproducibility, and histology is labor-intensive. It has been determined that measurements with 3-dimensional CBCT imaging are accurate and highly repeatable¹⁷.

3D reconstruction of teeth and bone, based on a cone beam computed tomography image, continues to be tested with different segmentation methods. One processing algorithm is the stepwise threshold, which puts markers on certain areas of the image to differentiate teeth and bone. First, a rough 3-dimensional model of the maxillofacial complex is produced by the computer, and

then the maxilla and mandible are each identified to separate them from the teeth. An adequate stepwise threshold is imperative for cone beam computed tomography compared to a medical spiral computed tomography machine to increase resolution without increasing radiation. This is achieved by ensuring high contrast and low noise¹⁸. Soft tissue contrast is generally low, and to increase it, one must increase the dose significantly. To limit the negative effects on the patient would require a post-patient collimation, which would also limit scatter and noise.

Currently, cone beam computed tomography is the most accurate tool to determine if forces should be stopped or adjusted because there is orthodontic-induced inflammatory root resorption^{9,10}. Patients were assessed near the end of orthodontic treatment for the presence and severity of root resorption, and it was determined that there are significant differences in severity detected between panoramic radiographs and cone beam computed tomography. Panoramic radiographs underestimate root resorption after orthodontic tooth movement, have a lack of reproducibility, and roots of proclined teeth are often not imaged as they are outside the panoramic focal trough¹⁰. Cone beam computed tomography is used in humans because of the low radiation and high diagnostic quality, but in small animal models, micro-computed tomography is generally the chosen imaging modality. Resorption can be observed in real-time with micro-computed tomography¹⁹.

Artificial Intelligence

New computer techniques are being applied in dentistry, and they are beneficial for the diagnosis and treatment planning in orthodontics²⁰. Machine learning and deep learning, parts of artificial intelligence, are methods of responding to computer algorithms based on the amount of data input. Convolutional neural networks of artificial intelligence are based on biological neural networks of the brain. Many neurons are connected by a similarity and then put into one layer of the network. This new layer rewires a new neural network, and a second layer is formed. Between the first and last layers of the convolutional neural network, the middle layers are the ones that have learned how to make decisions and identify pictures.

The more complex the task for the artificial intelligence, the greater the number of middle layers it will need to learn²¹. Making the input method and building the layers of machine learning can be easy, but analyzing the data output can be more complicated. The goal is that the artificial intelligence will be fully developed and user-friendly enough for a clinician to use in their daily practice²². Artificial intelligence has evolved to be so sophisticated that it can consume and recognize patterns in data, potentially better than humans. It is cost-effective and time-efficient, and it will become increasingly more useful in the future²². When developing a new artificial intelligence algorithm, human intelligence is the control and gold standard. Kunz et. al. created an automated cephalogram using an artificial intelligence algorithm, which had almost no statistically significant results, and the differences between the machine and the human gold standard were not clinically relevant²³.

Using segmentation to differentiate the teeth from the surrounding craniofacial structures will allow better visualization of crown and root positioning and will allow the orthodontist to have a better chance at ideal and predicted outcomes of treatment. Machine learning, creating different layers for each diagnostic variable, can teach artificial intelligence to provide exact diagnoses and treatment plans for each specific malocclusion. However, artificial intelligence has no intuition, so the

orthodontist has to input a significantly large amount of information for it to recognize and learn the patterns¹⁵. When evaluating a new artificial intelligence for segmentation of panoramic radiographs, Leite et. al. used two deep convolutional neural networks with expert refinement and found a significant reduction in time versus using manual segmentation²⁴. This model was highly accurate and performed very quickly to detect and segment teeth. One network detects teeth, and the other fine-tunes segmentation. The operator must place seed points and boundaries, adjust contrast, and trim edges to build a segmentation map based on whether the pixels were correctly included. A limitation of their model was that it incorrectly identified missing teeth with a replacement bridge, overlapped teeth, and retained primary teeth²⁴.

It is labor-intensive to manually segment a cone-beam computed tomography image²⁴⁻²⁶, so another automated tooth segmentation tool was developed based on a feature called a pyramid network²⁴. In a segmentation study of tooth pulp cavities for better identification, grayscale was used to find the optimal segmentation threshold after the pulp cavity was manually outlined. In 2018, this was more accurate and complete than other methods of segmentation²⁷. Training and validating a mixed-scaled dense convolutional neural network was attempted for multiclass segmentation instead of only binary segmentation, and it achieved similar accuracy²⁸. These advances are all made to reduce the amount of time needed by the clinician and turn the focus back to the actual patient. Chen et al., in *The Angle Orthodontist*, the maxillary structure was auto-segmented to assess structural variations in the anatomy of canine impactions²⁹. Learning-based multi-source IntegratiON framework for Segmentation (LINKS) was used with cone beam computed tomography to quantify volumetric skeletal discrepancies. The segmentations allow for fast diagnosis and treatment planning of the need for skeletal expansion in these cases²⁹.

When treatment planning for craniomaxillofacial deformity patients, a majority voting method was used to estimate the segmentation map to train the first layer of the random forest classifier, update the maps, and then train the next layer. This was validated based on manually segmented ground truth. Other methods may not be able to handle pathological cases or those that differ from the norm, as this method does. A downfall is that there was only a small sample size and an even smaller number of patients with metal restorations to try to accurately segment³⁰. A deep learning approach to auto-segmentation using faster regions with a convolutional neural network tries to detect and number teeth in periapical radiographs. This method was able to account for teeth that overlap and may be counted twice, as well as missing teeth, and can number the teeth. Since manual radiographic interpretation is neither time efficient nor does it have high inter-examiner reliability due to personal differences, this approach shows that machines are inherently at the same level as novice clinicians. A fallback is that the teeth with a lot of similarity were difficult for the neural network to number correctly. It performed very well at detecting teeth and their position²⁵. Another proposed method for tooth segmentation is using occlusal contacts as reference points and transforming the Radon to separate adjacent teeth. The mesh model is segmented based on the Radon transform information that was extracted from all overlapping occlusal contacts. That information was gathered by using threshold and fast marching watershed methods. The accuracy and efficiency of this method were "promising"³¹.

Machine learning can provide high-quality diagnosis and treatment planning in orthodontics because the outcomes it produces are objective and predictable. It has four main uses in orthodontics: classification of the skeletal maturity indicators for prediction of growth status,

regression tasks for therapeutic treatment plans for extractions, automated detection of useful landmarks, and acquisition of tooth segmentation³². The watershed algorithm was used for automated tooth segmentation in rodents to show that contralateral teeth can be useful for comparing orthodontic tooth movement and orthodontically induced root resorption. The maxillary first molar was protracted and scanned before and after protraction with micro-computed tomography. The protracted roots had lower resulting volumes, and the contralateral roots had volumes comparable to those before the scan. Orthodontic tooth movement was determined to have no linear association with root resorption, and automated segmentation is more efficient than manual segmentation³³. On the contrary, Orhan et. al., set out to verify the performance of artificial intelligence using a deep convolutional neural network to detect apical pathosis compared to manual segmentation of cone beam computed tomography. They realized that there was no significant difference between the two detection methods³⁴. Clinicians should be cautious when adopting this artificial intelligence technology to avoid any possible medical-legal issues since there are no defined guidelines yet. A problem with some of the animal models is that they're using the same springs that are being used in humans. That amount of force is too much pressure on a rat's tooth and bone, which might explain why they experience so much resorption in those cases. Further research should be done to test the same hypotheses with a custom spring for the rodents.

When assessing the 2-dimensional images used to diagnose root resorption and root shape, the shape was determined to be harder to see on a panoramic radiograph, and it overestimated root resorption. Periapical and panoramic radiographs both have magnification errors, but the panoramic radiographs had more errors, and they were not magnified enough to see the cemento-enamel junction to determine root length. This information comes from only one radiograph machine from one office, so the methods could be repeated elsewhere to give the results more support¹¹. When root resorption was quantified on human teeth with light, 25g, and heavy, 225g, forces by using contralateral comparisons, scanning electron microscope images showed that heavier forces caused root resorption. Something to consider is that the teeth may have been tilted and not scanned in the same orientation each time, so a greyscale shading correction technique was employed to account for this³⁵. Another study that compared the same light and heavy forces in humans also concluded that there was less root resorption with lighter forces. There was twice as much movement with a heavier force, which is a contributing factor to resorption. Also noted was that resorption was greater in the maxilla and on the buccal surface³⁶. Those light and heavy forces were used once again and applied as rotational forces and analyzed with volumetric software. Again, heavy forces created more resorption than light ones, and the compression side of the root had more resorption than the tension side. Rotational correction is hard to correct and has the highest relapse, so it requires orthodontic forces and retention for a longer period of time, which can lead to more root resorption³⁷.

The most ethical way to do human in vivo studies is by observing premolars that are already planned for extractions before or during orthodontic treatment. This way, there is no damage to healthy teeth that are to be retained. Irregularly shaped and short roots are more susceptible to external surface resorption. However, when the applied pressure is below the threshold of movement, then root resorption stops⁷. Again, experimental premolars and contralateral controls were evaluated for root resorption after orthodontic tooth movement using periapical radiographs and micro-computed tomography. There was a significant difference in the test and control teeth,

but there was still root resorption in the controls. Generally, root resorption was underestimated in periapical films and had some false positives when the micro-computed tomography scans had none. The periapicals have high specificity and low sensitivity for identifying root resorption³⁸. Cone beam computed tomography before and after orthodontic treatment detected root resorption in every patient at 46% of all roots tested. The root was measured from the incisal edge to eliminate the previously mentioned trouble of repeatedly determining the location of the cemento-enamel junction⁸. When observing the changes of bone during root resorption and measuring certain parameters on the compression and tension sides of the root, we see resorption mostly in the apical region on the compression side of the root¹⁹.

Segmentation

Segmentation in orthodontics refers to the process of separating each structure from a CBCT into individual parts for exporting and manipulation. Cone beam computed tomography segmentation is becoming essential for accurate and efficient orthodontic diagnosis and treatment planning^{28,30}. There are plenty of semi-automated segmentation methods that require the clinician to adjust or refine after the computer does the gross segmentation. More studies are starting to be aimed at creating a fully automated method to segment both jaws and teeth simultaneously²⁸. An important consideration is that artifacts and radiographic noise make the segmentation process difficult^{24,30,39} as well as the way in which the data is gathered⁴⁰. Statistics, machine learning, and artificial intelligence take human error out of making a diagnosis that will dictate treatment and, essentially, the treatment outcome. The general use of clinical decision support systems is not routine in dentistry yet. One instance found a high correlation between cases that were treated with extractions and the computer's decision to treat them with extractions as well²⁰. The new artificial intelligence methods of segmentation and root resorption detection that are being developed have high accuracy and low time requirements compared to manual methods^{26,29,41}. They take seconds to minutes for the output rather than five to six hours for the preceding manual results.

Although artificial intelligence has excellent performance with tooth detection overall, it is more difficult for it to segment multirrooted teeth²⁴. Once this segmentation is possible and reliable, it will simplify studying the tooth root tissue changes in orthodontics²⁶. It could be used to plan biomechanics as well. Some clear aligner companies are already using this technology to fabricate their appliances¹⁵.

Deep learning continues to evolve over time and with the use of different input methods. The aim is to have computers automatically detect and identify pictures faster and more accurately than humans. Each new algorithm has pros and cons, but the consensus is that machines can learn and execute these techniques better than humans. The various AI-based machine learning and deep learning networks can segment even in the presence of artifacts. Clinicians should be aware of the challenges and find ways to manually work around them or include them in their treatment¹⁴. Most studies are a 2-dimensional assessment of hard tissue. They're also not automatic or fully automated; they're simply using a machine to reduce the work of the human expert³³. The drawback of routine usage of these methods of machine learning and execution is the cost and amount of radiation¹¹. Although CBCT is less expensive and has less radiation than medical-grade computed tomography scanners, most clinicians who already have their methods of obtaining radiographs might not think it is worth the extra expense.

Significance

Sometimes it takes a multidisciplinary approach to determine whether root resorption is caused by orthodontic forces or genetic determinants. Either way, the teeth with resorbed roots should be retained as long as the patient knows all the options, risks, and benefits⁴². Orthodontic tooth movement inevitably causes root resorption and can affect the success of the treatment. Force magnitude plays a large role in orthodontic-induced root resorption. If the force is too much for the periodontal ligament, then it could cause tissue ischemia, leading to root resorption. The direction of the force will determine the side of the root that is being resorbed³⁷. Although significant progress has been made in bone segmenting for diagnostic and treatment planning in orthodontics, much work needs to be done in accuracy and specifically developing algorithms that can predict root resorption.

Specific Aims

Our aims continue to evolve, but for this project they were threefold: to develop a program for calculating tooth volumes and establishing the normal volumes for each tooth, to develop a program to compare the pre-treatment and post-treatment tooth volume and to calculate the root volume loss, and to develop machine learning tools for quantification of root volume from segmented CBCT images.

METHODS

Screened the 1,182 Anatomage™ segmented CBCT models (Anatomodels) of orthodontic patients at the University of Florida Department of Orthodontics. These CBCTs were obtained with the i-CAT 3D Dental Imaging System (Xoran Technologies, Ann Arbor, Michigan) at 0.3mm resolution. From these 1,182 anatomodels, 100 cases with normal teeth anatomy were selected. CBCT images of these 100 cases were segmented using Diagnocat (Diagnocat, LLC, Reno, Nevada). Segmented individual teeth were exported in STL file format. Manual root segmentation from the crown was completed in Meshmixer (Autodesk, Toronto, Canada). We selected 127 for a pilot study to train the machine. The original dataset was split into 70% of the data being used for training the model and writing the code, and the other 30% was the validation set, which is used to fine-tune the parameters of the code. This will evaluate the machine learning model's performance to simulate real-world data as we are almost ready to deploy an application to the public. This study adhered to ethical guidelines for the use of patient data, ensuring confidentiality and anonymity. Appropriate approval from the University of Florida IRB was sought before data collection.

Inclusion Criteria

Subjects were included in the study if they had a CBCT taken for orthodontic purposes before initiating treatment and were in full permanent dentition (except third molars). We selected cases that had teeth with normal anatomy.

Exclusion Criteria

Subjects were excluded if they had any craniofacial deformity or abnormality, malformed teeth, or missing teeth except for 3rd molars.

Data Preparation

The dataset, comprising various measurements from STL files of teeth, was first refined to ensure relevance and accuracy for the project. In the root resorption classification program, we employed the **train_test_split** method to divide our dataset into training (70%) and testing (30%) sets, with a focus on the “Root/Crown Ratio (%)” as the primary feature and root resorption categories as the target. This split, executed with a **random_state** of 42 for consistency and reproducibility, was crucial for evaluating the model's predictive accuracy in a controlled yet realistic setting. This methodology not only facilitated the model's learning from a substantial portion of the data but also ensured an unbiased assessment of its performance on unseen data, a key factor in determining its applicability and reliability in clinical dental practice.

STUDY DESIGN

Root/Crown Ratio

Our machine learning tool provided more accurate datasets for each tooth on the backend to better utilize the GUIs. The root-to-crown ratio (R/C) is a critical metric in dental diagnosis, providing insights into the structural integrity and health of teeth. Traditionally, R/C calculation involves manual measurements, which are time-consuming and subject to inter-observer variability. To address these limitations, we developed a machine learning (ML) approach for automating R/C calculation and categorization into three distinct classes: normal, moderate, and severe RR. We started with STLs of tooth #8 to begin writing the program and will expand to all the teeth once we determine the model's accuracy. Before model development, manual annotations were performed to delineate tooth boundaries and label areas of interest (root and crown) for training.

Model Selection

The Random Forest Classifier was selected as the predictive model for classifying teeth based on the severity of root resorption (normal, moderate, severe). This choice was informed by the model's proven efficacy in handling complex datasets with a mix of categorical and continuous variables, as well as its robustness against overfitting. Moreover, by aggregating the results of numerous decision trees, Random Forests provides high accuracy and maintains good performance even with imbalanced datasets, a common issue in medical data.

Hyperparameter Tuning: Grid Search

A Grid Search approach was utilized to optimize the Random Forest model for hyperparameter tuning. This involved systematically exploring a range of parameter values to determine the most effective combination for our specific dataset. The parameters adjusted during this process included:

- **n_estimators**: The number of trees in the forest. Varying numbers were tested to identify a count that balanced performance and computational efficiency.
- **max_depth**: The maximum depth of each tree. Different depths were explored to prevent overfitting and ensure each tree captures the underlying patterns without being overly specific.

- **Min_samples_split**: The minimum number of samples required to split an internal node. Adjusting this parameter helped determine the optimal complexity of the trees.
- Other parameters like **min_samples_leaf** (the minimum number of samples required at a leaf node) and **max_features** (the number of features to consider when looking for the best split) were also part of the grid search, ensuring a comprehensive exploration of the model's configuration space.

The best parameters were: 'n_estimators': 10, 'max_depth': 10, 'min_samples_split': 2.

RESULTS

The decision tree in Figure 1 begins at the root node. It is the initial decision based on the R/C showing that a ratio ≤ 92.74 suggests a potential for severe root resorption. At the left subtree, there is a potential for severe resorption. The first left leaf node determines if the ratio is ≤ 80.81 ; the model predicts severe resorption with absolute certainty (gini = 0). At the right subtree, there is potential for the tooth to be classified as normal. The first right leaf node determines a R/C > 92.74 but ≤ 101.84 , still leading to a severe prediction but with less certainty (gini > 0). The second right leaf node has ratios > 101.84 , leading to a prediction of normal teeth. Notably, this threshold marks the beginning of the confidence interval for normal teeth, with a gini of 0, indicating high certainty.

The intermediate nodes all have a potential for moderate resorption, and nodes within the tree with a gini > 0 indicate less certainty and often correspond to moderate resorption. For example, the moderate nodes with a ratio > 92.74 but ≤ 98.9 lead to a prediction of moderate resorption with a gini of 0.5, indicating significant uncertainty and mixed classifications within this node. Further right, for ratios > 98.8 but ≤ 119.29 , the tree leans towards a normal classification but encounters moderate cases along the way (gini > 0).

When interpreting the severe threshold boundary, the decision tree suggests that an R/C ≤ 80.81 is indicative of severe root resorption, with the confidence decreasing as the ratio increases up to 92.74. Conversely, an R/C > 101.84 is indicative of normal roots with high certainty. As a general walkthrough of the leaf nodes, the leaves on the far left represent cases classified with high confidence as severe. The purity of these leaves (gini=0) indicated that these thresholds strongly indicate severe resorption. The leaves on the far right, particularly those with R/C values above 101.84, are pure (gini = 0) and predict normal roots, suggesting that high ratios are reliable indicators of normal root volume. Leaves in the middle of the tree have higher gini values, reflecting a mix of normal and moderate resorption cases. These nodes suggest moderate resorption occurs within a narrower and less distinctly defined range of R/C values.

STATISTICS

The performance of the Program 3 ML tool was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score for classification tasks. Table 1-1, 1-2, and 1-3. These metrics provided insights into the model's ability to accurately classify the severity of root resorption, an essential consideration in dental diagnostics and treatment planning. Accuracy measures the proportion of correctly classified instances in all instances. It is calculated as the ratio of correct predictions to the total number of predictions.

$$accuracy = \frac{TP + TN}{TP + FP + TN + FP} \quad (5-1)$$

Precision measures the proportion of true positive predictions among all positive predictions made by the model. It's calculated as the ratio of true positives to the sum of true positives and false positives.

$$precision = \frac{TP}{TP + FP} \quad (5-2)$$

Recall (Sensitivity) measures the proportion of true positive predictions among all actual positive instances in the dataset. It's calculated as the ratio of true positives to the sum of true positives and false negatives.

$$recall = \frac{TP}{TP + FN} \quad (5-3)$$

F1-score is the harmonic means of precision and recall, providing a balance between the two metrics. It's calculated as:

$$F1 \text{ score} = \frac{2 \times precision \times recall}{precision + recall} \quad (5-4)$$

By employing these evaluation metrics, we aim to comprehensively assess the performance of our ML model in accurately calculating R/C values and classifying them into relevant categories, thereby ensuring reliability and effectiveness in clinical applications.

Discussion:

It is accepted in orthodontics that light forces during treatment are the best way to avoid root resorption. Popular literature determines RR is unaffected by archwires or brackets, and if you detect RR, then it is best practice to pause treatment for 2-3 months⁶ and to limit the duration of treatment². In a time when orthodontics is becoming dependent on digital advances, it is now more predictable to have a proper, overall, and RR-specific diagnosis in 3 dimensions rather than the 2D images of the past¹⁵. Along with the 3D technological advances in orthodontics is artificial intelligence, which has evolved so much that it has a high potential to diagnose better than humans. The goal of incorporating AI into orthodontics is to make it intuitive enough for a clinician to use on a daily basis²². After attempting a literature review of publications including a volumetric 3D analysis of the R/C, we realized that it is lacking in this specific area. There were many studies like Anand et. al., which determined the R/C in 2D for normal maxillary central incisors to be 1.627 ± 0.04 ⁴³. Also, there was a study that looked at the volume of upper central incisors to determine if other abnormalities affected the volume, but this was still looking at the tooth as a whole and not separating the root volume⁴⁴.

Our project aimed to use segmented CBCT images to develop a machine-learning tool for the quantification of root volume. Automating R/C calculation through ML offers several clinical implications. Firstly, it streamlines diagnostic workflows by reducing the time and effort required for manual measurements. Secondly, the accurate categorization of R/C into normal and resorption classes enables early detection of RR, facilitating timely intervention and treatment planning. The

decision tree provides clear thresholds for normal roots and severe root resorption based on the R/C. These thresholds can serve as guidelines for preliminary assessments in dental practice, potentially streamlining the diagnostic process. Additional clinical evaluation and diagnostic methods are recommended for moderate cases where the model shows greater uncertainty. The programs can serve as educational tools for dental professionals, aiding in understanding the variability and presentation of root resorption cases. The discussion revolves around the performance of our two user-friendly GUIs, ML model, limitations, and future directions.

User-Friendly GUIs

These GUIs make ML algorithms will be made accessible to dental practitioners with varying technical expertise. GUIs can empower users to interact with the ML model effectively without requiring specialized training or programming skills by providing intuitive interfaces and clear instructions. This accessibility enhances the tool's usability and encourages its widespread adoption in clinical settings.

Performance of Machine Learning Model

The developed machine learning model demonstrated promising performance in accurately calculating R/C values and classifying them into predefined categories. Evaluation metrics such as accuracy, precision, recall, and F1-score indicated robust performance across different classification tasks. The high performance of the model suggests its potential utility as a reliable tool for assisting dental practitioners in R/C assessment.

Normal Roots Without Resorption

The high final precision indicated that when the model predicts a tooth as having normal roots, it is correct 92% of the time. The recall signifies that the model successfully identifies 96% of all normal cases. The F1-score, balancing precision and recall, suggests the model is highly reliable in identifying normal cases. The support is the number of normal instances in the test dataset.

Moderate Root Resorption

The precision indicates that the model correctly identifies moderate root resorption cases 86% of the time. Recall of the model shows that it identifies 76% of the actual moderate cases, indicating some cases might be missed or misclassified. The F1-score here points to a moderate level of accuracy and reliability for these cases, and the support is 17 cases of moderate root resorption in the test dataset.

Severe Root Resorption

The model shows perfect precision and recall, identifying every severe case correctly. The perfect F1-score indicated exceptional model performance in this category. Note that the support of 7 being a smaller sample size may impact the reliability of the 100% scores.

Overall Model Performance

Accuracy indicates that the model correctly classifies 92% of the cases across all categories. Macro Average Precision of 93% reflects the average precision across all categories, indicating a high

level of overall precision. Macro Average Recall of 90% across all categories is also high, demonstrating the model's effectiveness in identifying true cases. A high overall F1 score of 91% suggests a balanced model performance between precision and recall. Figure 2 is a Graphical representation of the dispersion of the data in the third pass.

Limitations

Potential limitations of this study include finding an expert in machine learning who is also an expert in dentistry in the research field, developing a novel assessment tool requiring an extreme amount of time and data input, and crown morphology was not considered in the data collection stage. Further refinement of the ML model, especially in improving the identification of moderate cases, is recommended. This could involve training with a larger dataset or integrating more diverse data sources.

Future Direction

Future research directions for this project involve continuing to expand the model to classify the other 27 teeth, validating the model using a separate holdout dataset to assess its generalization ability and robustness, combining the ML model with Program 2 to do a pre- and post-treatment analysis to quantify how much root volume has been lost during treatment, and seamless integration of the GUIs with existing clinical workflows. Additionally, future research could explore incorporating additional predictive variables, such as patient age, dental history, and genetic factors, to enhance model accuracy.

Conclusion

This project outlined the beginning of a comprehensive approach for developing and validating a machine learning-based application for automated R/C calculation and classification in dental imaging. By leveraging advanced ML techniques, we can enhance the efficiency and accuracy of dental diagnosis and treatment planning, ultimately improving patient care and outcomes. The machine learning model demonstrated significant potential as a diagnostic aid in the field of dentistry for root resorption severity classification. Its high overall accuracy and particular effectiveness in identifying normal and severe cases make it a valuable tool in clinical decision-making. Continued refinement and validation of the model are recommended to maximize its utility and reliability in diverse clinical settings. Once the ratio program is complete, it can be integrated with the comparison tool, and then the project would be to integrate that seamlessly with existing clinical workflows and software. While the developed tools show promising performance and clinical implications, further research and validation efforts are needed to address existing limitations and unlock their full potential.

References:

1. Pereira SA, Lopez M, Lavado N, Abreu JM, Silva H. A clinical risk prediction model of orthodontic-induced external apical root resorption. *Revista Portuguesa de Estomatologia, Medicina Dentária e Cirurgia Maxilofacial*. 2014;55(2):66-72.

2. Apajalahti S, Peltola JS. Apical root resorption after orthodontic treatment—a retrospective study. *The European Journal of Orthodontics*. 2007;29(4):408-412.
3. Fuss Z, Tsesis I, Lin S. Root resorption—diagnosis, classification and treatment choices based on stimulation factors. *Dental traumatology*. 2003;19(4):175-182.
4. Lopatiene K, Dumbravaite A. Risk factors of root resorption after orthodontic treatment. *Stomatologija*. 2008;10(3):89-95.
5. Owman-Moll P, Kurol J, Lundgren D. Effects of a doubled orthodontic force magnitude on tooth movement and root resorptions. An inter-individual study in adolescents. *European journal of orthodontics*. 1996;18(2):141-150.
6. Weltman B, Vig KW, Fields HW, Shanker S, Kaizar EE. Root resorption associated with orthodontic tooth movement: a systematic review. *American journal of orthodontics and dentofacial orthopedics*. 2010;137(4):462-476.
7. Leach H, Ireland A, Whaites E. Radiographic diagnosis of root resorption in relation to orthodontics. *British dental journal*. 2001;190(1):16-22.
8. Castro IO, Alencar AH, Valladares-Neto J, Estrela C. Apical root resorption due to orthodontic treatment detected by cone beam computed tomography. *The Angle Orthodontist*. 2013;83(2):196-203.
9. Freitas Jcd, Lyra OCP, Alencar AHGd, Estrela C. Long-term evaluation of apical root resorption after orthodontic treatment using periapical radiography and cone beam computed tomography. *Dental press journal of orthodontics*. 2013;18:104-112.
10. Dudic A, Giannopoulou C, Leuzinger M, Kiliaridis S. Detection of apical root resorption after orthodontic treatment by using panoramic radiography and cone-beam computed tomography of super-high resolution. *American Journal of Orthodontics and Dentofacial Orthopedics*. 2009;135(4):434-437.
11. Sameshima GT, Asgarifar KO. Assessment of root resorption and root shape: periapical vs panoramic films. *The Angle Orthodontist*. 2001;71(3):185-189.
12. Owman-Moll P. Orthodontic tooth movement and root resorption with special reference to force magnitude and duration. A clinical and histological investigation in adolescents. *Swedish dental journal Supplement*. 1995;105:1-45.
13. Perona G, Wenzel A. Radiographic evaluation of the effect of orthodontic retraction on the root of the maxillary canine. *Dentomaxillofacial Radiology*. 1996;25(4):179-185.
14. Shujaat S, Bornstein MM, Price JB, Jacobs R. Integration of imaging modalities in digital dental workflows—possibilities, limitations, and potential future developments. *Dentomaxillofacial Radiology*. 2021;50(7):20210268.
15. Retrouvey J-M, Abdallah M-N. *3D Diagnosis and treatment planning in orthodontics: an atlas for the clinician*. 2021.
16. Scarfe WC, Farman AG. What is cone-beam CT and how does it work? *Dental Clinics of North America*. 2008;52(4):707-730.
17. Chan EK, Darendeliler MA. Exploring the third dimension in root resorption. *Orthodontics & craniofacial research*. 2004;7(2):64-70.
18. Naumovich S, Naumovich S, Goncharenko V. Three-dimensional reconstruction of teeth and jaws based on segmentation of CT images using watershed transformation. *Dentomaxillofacial Radiology*. 2015;44(4):20140313.
19. Ru N, Liu SS-Y, Zhuang L, Li S, Bai Y. In vivo microcomputed tomography evaluation of rat alveolar bone and root resorption during orthodontic tooth movement. *The Angle Orthodontist*. 2013;83(3):402-409.

20. Elżbieta Machoy M, Szyszka-Sommerfeld L, Vegh A, Gedrange T, Woźniak K. The ways of using machine learning in dentistry. *Advances in Clinical & Experimental Medicine*. 2020;29(3)
21. Arık SÖ, İbragimov B, Xing L. Fully automated quantitative cephalometry using convolutional neural networks. *Journal of Medical Imaging*. 2017;4(1):014501-014501.
22. Dreyer KJ, Geis JR. When machines think: radiology's next frontier. *Radiology*. 2017;285(3):713-718.
23. Kunz F, Stellzig-Eisenhauer A, Zeman F, Boldt J. Artificial intelligence in orthodontics: Evaluation of a fully automated cephalometric analysis using a customized convolutional neural network. *Journal of Orofacial Orthopedics/Fortschritte der Kieferorthopädie*. 2020;81(1)
24. Leite AF, Gerven AV, Willems H, et al. Artificial intelligence-driven novel tool for tooth detection and segmentation on panoramic radiographs. *Clinical oral investigations*. 2021;25:2257-2267.
25. Chen H, Zhang K, Lyu P, et al. A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films. *Scientific reports*. 2019;9(1):3840.
26. Lahoud P, EzEldeen M, Beznik T, et al. Artificial Intelligence for Fast and Accurate 3-Dimensional Tooth Segmentation on Cone-beam Computed Tomography. *Journal Of Endodontics*. 2021;47(5):827-835.
27. Wang L, Li J-p, Ge Z-p, Li G. CBCT image based segmentation method for tooth pulp cavity region extraction. *Dentomaxillofacial Radiology*. 2019;48(2):20180236.
28. Wang H, Minnema J, Batenburg KJ, Forouzanfar T, Hu FJ, Wu G. Multiclass CBCT image segmentation for orthodontics with deep learning. *Journal of dental research*. 2021;100(9):943-949.
29. Chen S, Wang L, Li G, et al. Machine learning in orthodontics: Introducing a 3D auto-segmentation and auto-landmark finder of CBCT images to assess maxillary constriction in unilateral impacted canine patients. *The Angle Orthodontist*. 2020;90(1):77-84.
30. Wang L, Gao Y, Shi F, et al. Automated segmentation of dental CBCT image with prior-guided sequential random forests. *Medical physics*. 2016;43(1):336-346.
31. Xia Z, Gan Y, Chang L, Xiong J, Zhao Q. Individual tooth segmentation from CT images scanned with contacts of maxillary and mandible teeth. *Computer methods and programs in biomedicine*. 2017;138:1-12.
32. Liu J, Chen Y, Li S, Zhao Z, Wu Z. Machine learning in orthodontics: Challenges and perspectives. *Advances in Clinical and Experimental Medicine*. 2021;30(10):1065-1074.
33. Trelenberg-Stoll V, Drescher D, Wolf M, Becker K. Automated tooth segmentation as an innovative tool to assess 3D-tooth movement and root resorption in rodents. *Head & face medicine*. 2021;17:1-9.
34. Orhan K, Bayrakdar I, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. *International endodontic journal*. 2020;53(5):680-689.
35. Chan EK, Darendeliler MA, Petocz P, Jones AS. A new method for volumetric measurement of orthodontically induced root resorption craters. *European journal of oral sciences*. 2004;112(2):134-139.
36. Paetyangkul A, Türk T, Elekdağ-Türk S, Jones AS, Petocz P, Darendeliler MA. Physical properties of root cementum: part 14. The amount of root resorption after force application

- for 12 weeks on maxillary and mandibular premolars: a microcomputed-tomography study. *American Journal of Orthodontics and Dentofacial Orthopedics*. 2009;136(4):492. e1-492. e9.
37. Wu AT, Turk T, Colak C, et al. Physical properties of root cementum: Part 18. The extent of root resorption after the application of light and heavy controlled rotational orthodontic forces for 4 weeks: A microcomputed tomography study. *American Journal of Orthodontics and Dentofacial Orthopedics*. 2011;139(5):e495-e503.
 38. Dudic A, Giannopoulou C, Martinez M, Montet X, Kiliaridis S. Diagnostic accuracy of digitized periapical radiographs validated against micro-computed tomography scanning in evaluating orthodontically induced apical root resorption. *European journal of oral sciences*. 2008;116(5):467-472.
 39. Reitz I, Hesse B-M, Nill S, Tücking T, Oelfke U. Enhancement of image quality with a fast iterative scatter and beam hardening correction method for kV CBCT. *Zeitschrift für Medizinische Physik*. 2009;19(3):158-172.
 40. Bai T, Yan H, Ouyang L, et al. Data correlation based noise level estimation for cone beam projection data. *Journal of X-ray Science and Technology*. 2017;25(6):907-926.
 41. Zheng J, Zhang D, Huang K, Sun Y. A CBCT series slice image segmentation method. *Journal of X-Ray Science and Technology*. 2018;26(5):815-832.
 42. Kokich VG. Orthodontic and nonorthodontic root resorption: their impact on clinical dental practice. *Journal of Dental Education*. 2008;72(8):895-902.
 43. Anand R, Sarode SC, Sarode GS, Patil S. Human permanent teeth are divided into two parts at the cemento-enamel junction in the divine golden ratio. *Indian Journal of Dental Research*. 2017;28(6):609-612.
 44. Aras I, Bavbek NC, Kaya B, Aras A. Three-dimensional digital evaluation of tooth symmetry and volume in patients with missing and peg-shaped maxillary lateral incisors. *American Journal of Orthodontics and Dentofacial Orthopedics*. 2022;162(2):e82-e95.

Figures:

Figure 1. Random Forest of classifications

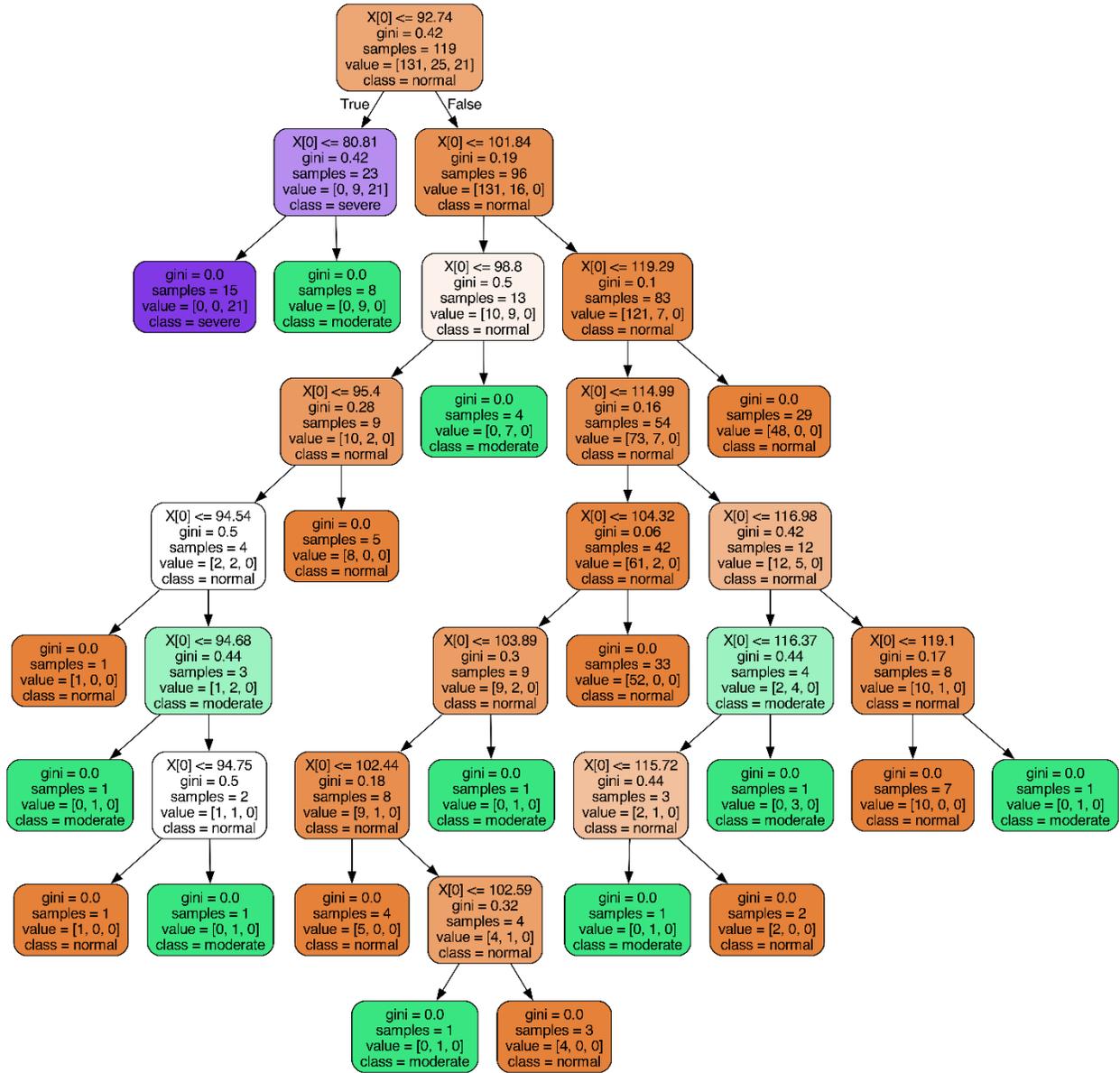
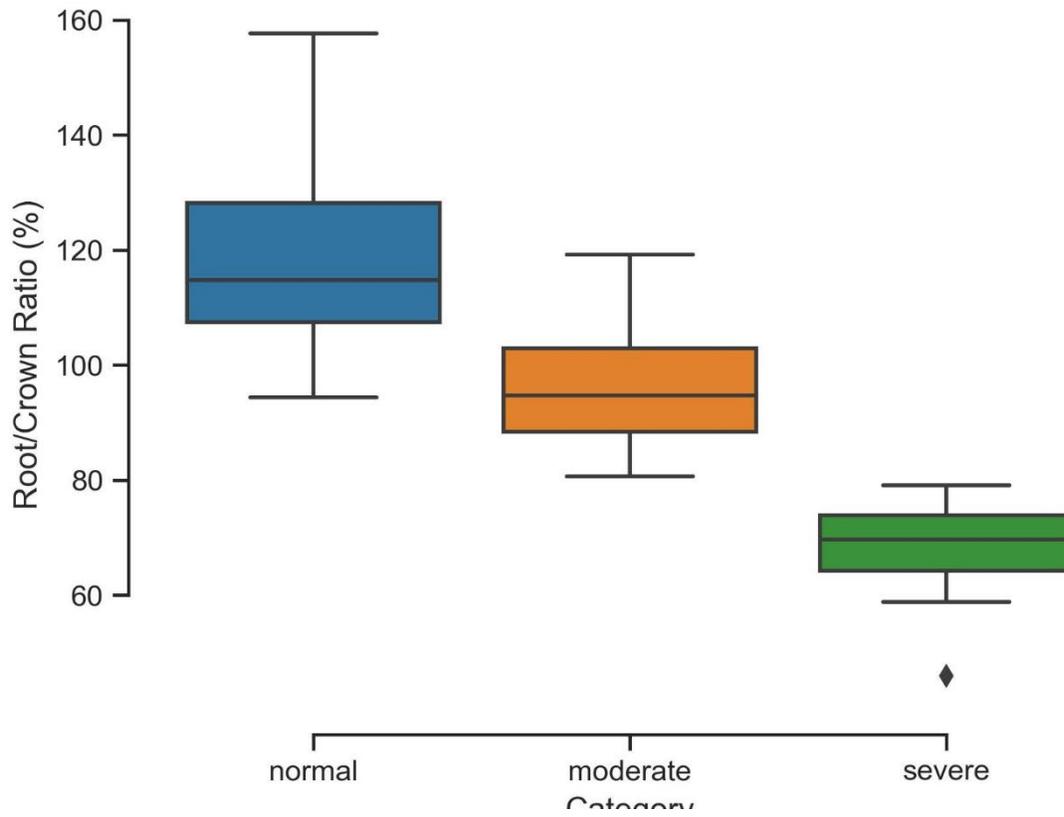


Figure 2. Graphical representation of the dispersion of the data in the third pass.



Tables:

Table 1-1. First test of the root/crown ratio program.

	Precision	Recall	F1-Score	Support
Normal	0.76	0.83	0.79	53
Moderate	0.31	0.29	0.30	14
Severe	0.25	0.12	0.17	8
Accuracy			0.65	75

Table 1-2. Second test of the root/crown ratio program.

	Precision	Recall	F1-Score	Support
Normal	0.85	0.92	0.88	50
Moderate	0.80	0.44	0.57	18
Severe	0.63	1.00	0.77	7
Accuracy			0.81	75

Table 1-3. Third test of the root/crown ratio program.

	Precision	Recall	F1-Score	Support
Normal	0.92	0.96	0.94	53
Moderate	0.86	0.76	0.81	17
Severe	1.00	1.00	1.00	7
Accuracy			0.92	77
