



**AUTOMATED DIAGNOSIS IN X-RAY DENTAL DATA: INNOVATIVE SYSTEM  
DEVELOPED WITH SEGMENTATION AND CLASSIFICATION METHODS**

**MSc Thesis**

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**AUTOMATED DIAGNOSIS IN X-RAY DENTAL DATA: INNOVATIVE  
SYSTEM DEVELOPED WITH SEGMENTATION  
AND CLASSIFICATION METHODS**

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DEVELOPED WITH SEGMENTATION AND CLASSIFICATION METHODS

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28 August 2024

We certify that we have read this dissertation and that in our opinion it is fully adequate,  
in scope and in quality, as a dissertation for the degree of Master of Science.

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I hereby declare that all information in this document has been obtained and presented in accordance with the academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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## LIST OF SYMBOLS

**kVp** : Voltage  
= : Equal  
+ : Addition  
% : Percentage  
/ : Division



## ABBREVIATIONS

<b>R-CNN</b>	: Region-based Convolutional Neural Network
<b>AI</b>	: Artificial Intelligence
<b>ML</b>	: Machine Learning
<b>CBCT</b>	: Cone Beam Computed Tomography
<b>CNN</b>	: Convolutional Neural Network
<b>MRI</b>	: Magnetic Resonance Imaging
<b>PBL</b>	: Periodontal Bone Loss
<b>DXRI</b>	: Dual-Energy X-ray Absorptiometry Imaging
<b>DNN</b>	: Deep Neural Networks
<b>OFC</b>	: Orofacial Clefts
<b>AUC</b>	: Area Under the Curve
<b>CBIR</b>	: Content-Based Image Retrieval
<b>CLU</b>	: Cluster
<b>FOF</b>	: Feature of Features
<b>LBP</b>	: Local Binary Patterns
<b>ROI</b>	: Region of Interest
<b>FCM</b>	: Fuzzy C-Means
<b>NFCM</b>	: New Clustering Approach
<b>FP</b>	: False Positive
<b>DDS</b>	: The Dental Diagnosis System
<b>DRLSE</b>	: Deformable Region-based Level Set
<b>FMM</b>	: Fast Marching Method
<b>MIC</b>	: Maximum Iso Center
<b>SLR</b>	: Systematic Literature Review
<b>IEEE</b>	: Institute of Electrical and Electronics Engineers
<b>ACM</b>	: Association for Computing Machinery
<b>NASNet</b>	: Neural Architecture Search Network
<b>OPG</b>	: Orthopantomogram
<b>YOLOv3</b>	: You Only Look Once version 3
<b>BDR</b>	: Collapsed Root Canal Treatments
<b>GLCM</b>	: Gray Level Co-Occurrence Matrix
<b>GLDM</b>	: Gray Level Difference Method
<b>ANOVA</b>	: Analysis of Variance
<b>SVM</b>	: Support Vector Machine
<b>DXI</b>	: Digital X-ray Image
<b>VGG</b>	: Visual Geometry Group
<b>ResNet</b>	: Residual Network
<b>DenseNet</b>	: Densely Connected Convolutional Networks
<b>K-NN</b>	: K-nearest Neighbor
<b>AM</b>	: Pre-mortem
<b>PM</b>	: Post-mortem
<b>FPN</b>	: Feature Pyramid Network
<b>PSPNet</b>	: Pyramid Scene Parsing Network
<b>CSV</b>	: Comma-Separated Values
<b>LDA</b>	: Linear Discriminant Analysis
<b>MAD</b>	: Mean Absolute Distance
<b>HTML</b>	: HyperText Markup Language
<b>TP</b>	: True Positive

**SMP** : Segmentation Models PyTorch  
**HTGkFCM** : Hierarchical Transductive Granular k-Nearest Neighbor Classifier  
with Fuzzy C-Means



# X-RAY DENTAL VERİLERİNDE OTOMASYONLU TANI: SEGMENTASYON VE SINIFLANDIRMA YÖNTEMLERİ İLE GELİŞTİRİLEN YENİLİKÇİ SİSTEM

## ÖZET

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Yapay zeka teknolojilerinin sağlık dünyasındaki ilerlemesi, insan hata payını azaltma ve erken teşhis sağlama potansiyeli nedeniyle büyük önem taşıyor. Projemizde diş muayenelerini optimize etmek, otomatikleştirmek ve hızlandırmak için yapay zeka modelleri geliştirildi. Bu sayede diş röntgenlerinde tanısal doğruluğun en üst düzeye çıkarılması amaçlanmaktadır. Aynı zamanda diş hekimliği fakültesi öğrencileri için de bir eğitim depo alanı oluşturulması hedeflenmiştir, böylelikle öğrencilerin eğitim hayatlarında kullanabilecekleri bir simülasyon sistemi oluşturulabilecektir.

Projede öncelikle amaca yönelik veri seti oluşturmaya başladık. En doğru ve uygun veri setini oluşturmak için kapsamlı bir tarama çalışması yapıldı. Bu süreçte etik kurul kurallarına uyuldu. Veriler Kaggle gibi herkese açık platformlar kullanılarak toplandı. Doğru veri setini oluşturmak, bir projeye başlamadan önce hesaplanması ve ayarlanması gereken kısımdır. Doğru veri seti amaçlı olmalı ve ne kadar çok veri varsa o kadar iyi test edilebilir. Bu nedenle projemizde en çok çaba harcadığımız kısımlardan biri veri seti oluşturmaktı. Özellikle tıp alanında, diş röntgen görüntü analizinde kullanılmak üzere yüksek kaliteli ve güvenilir veri setleri elde etmek zorlu bir süreçtir. Bu projede, veri toplama kurulumunda en iyi yaklaşımı ve uyarlanabilir bir yöntemi kullanmaya özen gösterildi. Öncelikle, farklı veri setleri açık kaynakta kullanılabilirlik açısından değerlendirildi ve bunlardan biri genel bir veri seti verdiği ve böyle bir setle modeli genelleştirmek mümkün olduğu için seçildi. Bunlar diş sağlığında tipik durumlardır ve bu nedenle normal popülasyon için referans görevi görebilir.

Projede X-ray diş röntgen görüntülerinden oluşan veri setleri üzerinde U-Net segmentasyon yöntemi uygulandı. Elde edilen segmentasyon sonuçları Faster R-CNN sınıflandırma yöntemleri ile dört farklı kategori (kavite, gömülü diş, implant, dolgu) üzerinde çalışılarak analiz edildi. Bu modeller diş röntgenindeki çürük, gömülü diş, implant ve dolgu gibi unsurları saniyeler içinde tespit edip tam konumlarını belirleyebilmektedir.

Geliştirdiğimiz yapay zeka modelleri için kullanıcı dostu bir arayüz oluşturuldu. Bu arayüz hastalar ve doktorlar için ayrı giriş ekranları sunar. Hasta giriş ekranı üzerinden hastalar hızlı bir şekilde röntgen tetkiklerini yaptırabilirken, doktor giriş ekranı üzerinden doktorlar da hastaların röntgenleri hakkında yorum yapıp teşhis koyabiliyor.

Model üzerinde yapılan F1 skor testleri sonucunda %91 doğruluk oranı elde edilmiştir. Gelecekteki çalışmalar bu doğruluk oranının artırılmasına ve daha detaylı analizlerin yapılmasına odaklanacaktır.



Anahtar sözcükler: Segmentasyon, Sınıflandırma, Röntgen Diş Görüntüleri, Diş Muayene Optimizasyonu

# **AUTOMATED DIAGNOSIS IN X-RAY DENTAL DATA: INNOVATIVE SYSTEM DEVELOPED WITH SEGMENTATION AND CLASSIFICATION**

## **ABSTRACT**

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The advancement of artificial intelligence (AI) technologies in the healthcare world is of great importance with its potential to reduce the margin of human error and provide early diagnosis. In our project, AI models were developed to optimize, automate and accelerate dental examinations. In this way, it is aimed to maximize the diagnostic accuracy in dental x-rays. At the same time, it is aimed to create an educational storage area for dentistry faculty students, so that a simulation system can be created that students can use in their educational lives.

In the project, first we started to create a dataset for the purpose. An extensive scanning study was carried out to create the most accurate and appropriate dataset. Ethics committee rules were followed during this process. Data were collected using public platforms such as Kaggle. Creating the correct dataset is the part that needs to be calculated and adjusted before starting a project. The right data set should be purposeful and the more data there is, the better it can be tested. For this reason, one of the parts where we spent the most effort in our project was creating the data set. Especially in the medical field, obtaining high quality and reliable data sets for use in dental x-ray image analysis is a challenging process. In this project, care was taken to use the best approach and an adaptable method in data collection setup. First of all, different data sets were evaluated for usability in open source, and one of them was chosen because it gave a general data set and it was possible to generalize the model with such a set. These are typical situations in dental health and therefore can serve as a reference for the normal population.

In the project, the U-Net segmentation method was applied on data sets consisting of X-ray dental x-ray images. The segmentation results obtained were analyzed with Faster R-CNN classification methods by working on four different categories (cavity, impacted tooth, implant, fillings). These models can detect elements such as cavities, impacted teeth, implants and fillings in dental x-rays within seconds and determine their exact location.

A user-friendly interface has been created for the artificial intelligence models we have developed. This interface offers separate login screens for patients and doctors. While

patients can quickly get their x-ray analyzes via the patient login screen, doctors can comment on patients' x-rays and make diagnoses via the doctor login screen.

As a result of the F1 score tests performed on the model, a 91% accuracy rate was obtained. Future studies will focus on increasing this accuracy rate and performing more detailed analyses.



Keywords: Segmentation, Classification, X-Ray Dental Images, Dental Examination Optimization

## **CHAPTER 1**

### **1. INTRODUCTION**

#### **1.1. Problem Definition and Motivation**

This project aims to provide significant improvements in dental practice by using artificial intelligence and machine learning techniques. First of all, AI and ML techniques enable automatic analysis of dental X-ray images, increasing diagnostic accuracy. In this way, dentists can make faster and more accurate decisions, which enables patients to receive more effective treatment. In addition, the detailed and accurately labeled x-ray data created in the project will be used for educational purposes in dental faculties and will offer students the opportunity to work on real-world cases. This will contribute to better training of future dentists by improving the quality of education.

The project aims to reduce misdiagnosis rates by minimizing human error. In this way, patients will be protected from being exposed to unnecessary treatments and overall healthcare costs will be reduced. In addition, using automatic systems instead of manual analysis allows dentists to use their time more efficiently, shortening the examination time per patient and allowing them to serve more patients. Archiving digital x-ray images in a central system provides rapid access to patients' past medical records. This makes it easier to share patient information, especially between different doctors, and reduces repeat x-rays.

In conclusion, this project aims to provide an innovative and effective solution in the field of dentistry. The integration of artificial intelligence and machine learning techniques will provide great benefits in both clinical practices and educational processes. This project aims to improve the quality of patient care and overall healthcare by providing dentists with a reliable auxiliary tool in the diagnosis and treatment processes. It is also seen as an important step that will pave the way for broader applications of AI in healthcare.

In dental practice, manual analysis of dental x-ray images is a time-consuming and subjective process that requires high accuracy. This process may vary depending on the experience level of dentists and may lead to increased misdiagnosis rates. Incorrect diagnoses can lead to patients receiving unnecessary or incorrect treatments, loss of efficiency in healthcare, and increased costs. In addition, patients who consult different doctors have to have x-rays taken again, creating an additional burden for both the patient and the healthcare system.

This project aims to solve these problems by using artificial intelligence (AI) and machine learning (ML) techniques on dental x-ray datasets. AI and ML-based automatic analysis systems can assist dentists in diagnosis and treatment planning, provide educational data in dental schools, minimize misdiagnosis rates, and save time in dental examinations. Additionally, archiving digital x-ray images in a central system can increase continuity and efficiency in healthcare by eliminating the need for patients to have x-rays taken again when they see different doctors.

Current dental x-ray analysis methods require user-friendly automated systems that provide high accuracy and efficiency. This project aims to develop an artificial intelligence-based system that performs segmentation and classification on dental x-ray images and thus provides significant improvements in dental practice.

## **1.2. The Necessary Background**

### **1.2.1. X-ray technologies**

X-ray imaging technology has played an important role in the dental world and has greatly improved diagnostic processes. The first dental radiographs became possible towards the end of the 19th century. Shortly after discovering X-rays, Roentgen embarked on an effort to adapt this new technology to dental practice to image the internal structure of teeth. In 1904, the first dental radiograph was taken at Henry Louis. However, the X-ray devices used at that time had limited security and therefore posed risks for people exposed to this technology. Over time, radiographic techniques and devices were improved, and dentists continued to use this technology to better observe tooth and jaw structure. [1]

Dental radiography has enabled dentists to evaluate conditions such as tooth decay, gum disease, jaw bone structures, tooth roots and jaw joint. With the advancement of technology, advanced techniques such as digital radiography have emerged. These digital techniques offer advantages such as faster imaging, lower radiation doses, and the ability to store and share images digitally. This has made dental practices safer and more effective.

Dental radiography plays an irreplaceable role in the modern world of dentistry because it makes it possible to receive valuable information necessary for the assessment of patients' diseases and creation of treatment regimens. Several uses of distinctive imaging techniques is adopted for the diagnosis of the teeth, jaw and related tissues as well as to capture appropriate images. Dental radiography is a form of diagnosing disease prevalent in patients' mouth ranging from caries detection, assessment of the bone pattern, determination of occlusal relationships, position, and selection of favourable position for orthodontic appliances. This outline of content will include an introduction and review of the different types of dental radiography techniques commonly used in dental practice and their individual purposes in dental diagnosis and treatment planning.

**Periapical Radiography:** Periapical radiography shows a particular tooth with extreme views that extend from the crown to its root. It includes the area below the gum or alveolar crest line up to the apex of the roots; it also displays the tips of the roots, bone structures, and other adjacent structures. Some of the diagnostic applications of periapical radiography are in the diagnosis of dental caries, root lesion, apical infection and periodontal diseases.

**Bitewing Radiography:** Bitewing radiology is a type of radiographic image that catches the crown of teeth in both the maxilla and mandible. This method may be applied for detection of interdental cavities, as well as measuring the distance between two adjacent teeth, and for the assessment of the state of the gums. Bitewing periapical radiographs are often referred to as patients' general screening for periodontal diseases, and cavities.

**Panoramic Radiography:** Local enlargement allows each image to be magnified either in area or overall, giving an overall view of the upper and lower teeth, jaws, and any tissues that may be connected to or near the teeth. This technique makes it possible for the dentist to assess relations between the different teeth, confirmation and loss of the tooth, preparation for teeth extraction, configuration of the bones and the state of the temporomandibular articulation. It is also used to locate areas of infection, abscesses, cysts or tumors prior to and after different dental interventions.

**Cephalometric Radiography:** This technique involves the assessment of the spatial topology of the facial and jaw skeleton by means of the cephalometric radiography. It's a technique that has to do with the analysis of head and facial profiles when it comes to treatment planning in orthodontics. Cephalometry gives insights as to the growth and form of Jaw and Teeth besides the general Proportioning of the face.

**Tomography (CBCT):** Consequently, CBCT presents a valuable tool to the dentists providing them with a detailed, three dimensional view of the bone structure, tooth root structures and the tissues around the teeth. CBCT helps identify disorders in implantology, endodontics, and oral surgery with a high degree of efficiency.

These are the basic and most common techniques that are applied in dental radiography, however; there are more advanced techniques which apply in other situations or requirements.[2]

### **1.2.2. Ai in medical**

In recent decades, since the mid-1960s to be precise with the projects Dendral and MYCIN, the application of AI in the medical field has undergone a quiet revolution. The true success of this inception when combined with the improvements and developments overtime in the technological platform has brought to the medical world an uncharted realm. [3]

Modern life, including the recent Covid-19 pandemic, has shown that AI is now an irreplaceable part of medicine or a healthcare system. Especially considering the current state of the COVID-19 pandemic, which prevented traditional methods of vaccine creation from lasting years before coming to fruition, more significant forms of companies have been able to utilize artificial intelligence to greatly shorten the process. Aids from computational bioinformatics, data mining and machine learning techniques have helped in identifying vaccine candidates as a result of a rapid response in genetic information and the development of effective Covid-19 vaccines within 6-9 months. This demonstrates how the use of Artificial intelligence in the medical field has grown to be very significant.

This is a crucial aspect that enables AI to produce results that are almost free from any errors or flaws. Through learning with vast amounts of training data, they effectively reduce the human error rate and deliver higher accuracy. Also by helping to increase the speed of diagnosing diseases, AI helps to diagnose the diseases at early stages, hence helping to treat diseases which are in their early stages, thus helping to make the treatment processes efficient and also helping to increase the quality of patients' lives. The use of data recording in medicine is a vital step for both growth and training. Earlier in the education of medical students, they would require textbooks and case studies now they get different sorts of simulations and recorded data for practice. This helps the students to practice or put into practice more real-life situations basically in line with the theory that has been taught.

One of the greatest accomplishments throughout man's history is the medical imaging. As is borne out by this study, Artificial Intelligence is used by the self-driving cars to sort through such images rapidly. Scans are not only made in a few seconds but also analyzed by more complex algorithms, which enables the doctors to diagnose illnesses more accurately as well as in the shorter time. This takes a lot of burden off the thought process

of treatment and makes the enzymatic unamalgamatic or patient treatment procedural less complicated.

Except for what has been posed today, the role of AI in medicine is vast and indicates potential future patterns of healthcare. Through rich data analysis and with the help of machine learning, radical improvements are being made towards making treatments more proactive and efficient as possible so as to make healthcare more affordable and feasible in the long run. Machine learning we find still maintains a central role within various alterations of the medical field that further enhances the overall patient experience.

Medical imaging is an important aspect in curative and diagnostic process of diseases which uses devices like X-ray, MRI and CT scan. Collecting and analyzing such images through traditional approaches can sometimes be a tedious affair. Where there used to be traditional techniques, artificial intelligence (AI) comes as a new horizon for medical imaging practices with many benefits.

AI takes full advantage of computational power, algorithms as well as software to run extensive data analyses with considerable speed. When integrated with medical imaging, AI provides several key advantages: When integrated with medical imaging, AI provides several key advantages:

**Speed and Efficiency:** Given that it is not time-bound, AI can review and interpret vast medical image data to shorten the diagnosis and therapy time. This has got the advantage of being particularly valuable during exigent circumstances where fast decision making is inevitable.

**Precision and Accuracy:** One type of usage is the difference that can be found in analyzing data that is beyond human reasoning which can provide more accurate diagnoses. This is especially important in areas like, early detection, where the accuracy of the existed method is crucial and can be greatly complemented with the usage of AI systems.

**Automation and Diagnostic Assistance:** With AI, there is a possibility of using devices that can analyze pictures of the human body and write a report on its own. This should make it possible for healthcare professionals to spend more time in this process and time for attending to the patients.

**Personalized Medicine:** When data regarding the genetic and medical history of patients is integrated into the AI platform, specific treatment plans can be developed. This is

helpful to the patients because they can then be provided with better treatments depending on their genes and the responses they have had to the past treatments given to them.

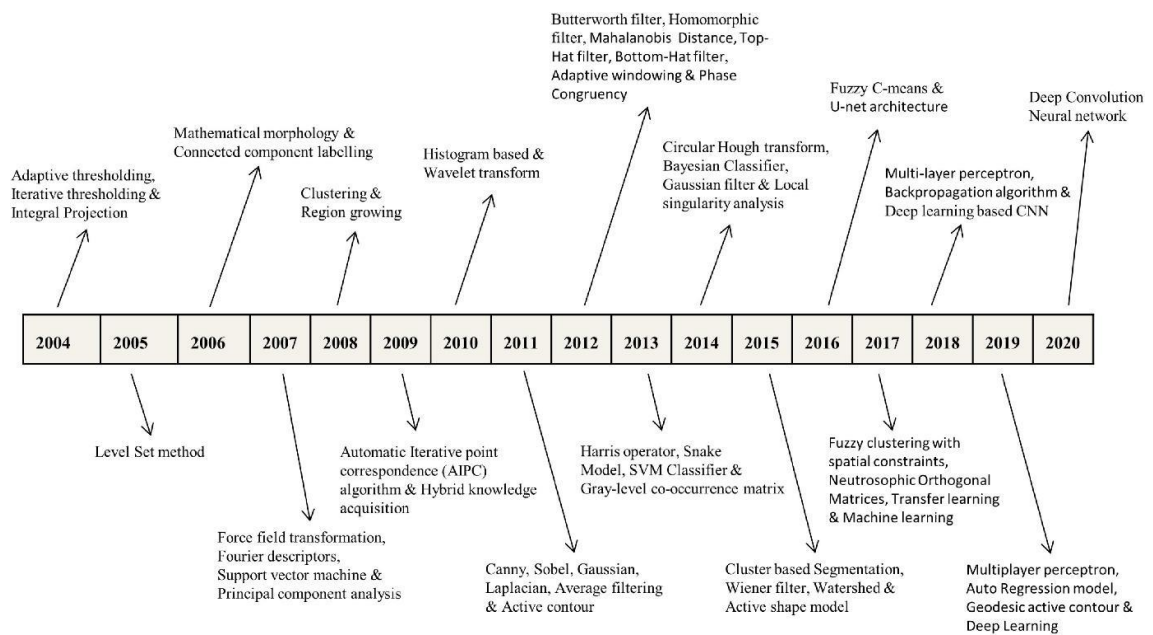
**Learning Capability:** Sophisticated AI systems have the builtin capacity for supervised learning as they are constantly trained on new data inputs. This ongoing learning enables, the systems to evolve over time, to perform effectively.

However, AI in medical imaging applications have some issues related to ethical concerns, security, and data privacy when integrating with the systems. Conquering these challenges, on the other hand, may usher in major advancements in medical imaging, which in turn shall increase patients' access to improved health care services.

### **1.2.3. Ai on the dental**

Among the wide areas of use of artificial intelligence technology, especially its integration into oral maxillofacial radiology, it has an important position in the field of dental health due to its ability to identify and label lesions that can escape the human eye. This technology offers dentists the opportunity to obtain more effective and reliable results by improving the diagnosis process quickly and precisely on radiographic images. Artificial intelligence contributes to the diagnosis and treatment processes in dentistry, allowing patients to have a better healthcare experience.

Artificial intelligence (AI) has recently been used in dentistry to find carious lesions in bitewing radiographs by means of pre-trained convolutional neural networks (CNNs). In terms of enhanced dependability, accuracy, and assessment time savings when used in panoramic radiography, CNNs may provide a higher diagnostic yield. [4]



**Figure 1.1:** Historical development of artificial intelligence in health[5]

#### 1.2.4. How to analyze dental x-ray images

The development of X-rays changed dentistry and provided a fresh perspective on how teeth are internally structured. However, radiation dosages were considerable and the equipment in use at the time was very antiquated. Growing technological advancements and a deeper comprehension of radiation have made dental radiography safe and commonplace in clinical settings.

Data collection from the patient is the first step in the analysis of X-ray dental images. The patient must be properly prepared before any dental x-rays can be taken. The potential radiation dangers are discussed with the patient, along with the significance of taking pictures prior to the radiography operation.

The dental or radiology staff positions the patient appropriately. To obtain reliable images, placement is essential. Dental radiography uses a variety of equipment. These consist of both extraoral and intraoral radiography equipment, such as panoramic X-ray machines and periapical and bitewing X-ray machines. The nature and intended use of the images will determine which gadget is best.

A film or digital sensor is inserted into the patient's mouth for dental radiography. This makes it possible for radiation to interact with the tissues around the teeth and produce

an image. Film is being replaced more and more by digital sensors due to the rapid usage of digital technology. Digital sensors can lower radiation exposure while enabling instantaneous image capture and digital format storage.

Dental radiography capture is a painstaking procedure that is essential to precise diagnosis and treatment planning. It takes a number of actions and methods to guarantee excellent images while reducing the radiation exposure that patients receive:

The first step in capturing a photograph is placing the patient. Accurate and diagnostically useful images can only be obtained when the patient is positioned correctly. The patient may lie down or be sat erect, depending on the sort of dental radiograph that is needed. Using positioning aids to stabilize the head and body reduces movement when taking pictures.

Subsequently, the X-ray equipment is calibrated and configured in accordance with the particular imaging method being employed. This involves determining the proper exposure duration, current, and voltage (kVp) for the X-ray tube. Collimation devices are another tool that can be used to focus the X-ray beam on the desired area of interest and spare nearby tissues from needless radiation exposure.

Throughout the whole image capture process, patient protection is given first priority. Thyroid collars and lead aprons are two options for protecting delicate tissues from radiation exposure. To reduce the radiation dosage to these organs, appropriate thyroid gland and gonadal shielding measures are also used. An X-ray film or digital sensor is inserted within the patient's mouth during intraoral radiography to take accurate images of each tooth and its supporting structure. Common intraoral radiography methods are bitewing and periapical radiography. While bitewing radiographs are used to concurrently visualize the crowns of the upper and lower teeth and detect interproximal caries, periapical radiographs offer thorough images of the complete tooth from crown to root.

By placing the X-ray film or digital sensor outside the patient's mouth, extraoral radiography allows for the larger-scale imaging of the oral and maxillofacial region. The use of cephalometric and panoramic radiography are common extraoral procedures. While cephalometric radiographs are utilized for orthodontic treatment planning to evaluate the skeletal and soft tissue structures of the face and jaws, panoramic radiographs offer a comprehensive assessment of the complete dentition, jaws, and surrounding structures in a single image.

The X-ray exposure is started, the subject and the machine are positioned correctly, and an image is taken. In film-based radiography, the latent image must be developed by processing the exposed X-ray film with chemical solutions in a darkroom. When using digital radiography, the image is quickly viewed and analyzed on a computer monitor or digital imaging equipment.

To guarantee the dependability and accuracy of dental radiography images, quality assurance procedures like routine equipment calibration, image processing inspections, and radiation dose monitoring are crucial. Maintaining high standards for image quality and patient safety also involves providing dental professionals with regular training and continuous education.

Dental practitioners can get high-quality radiographic images that help in the diagnosis and treatment planning of many oral health issues by using the right procedures and following established protocols.

Because dental professionals worldwide may employ dental X-ray imaging (DXRI) to detect anomalies in tooth structures, it has become the foundation for their work. [6]

The process of examining dental images included several phases of image improvement, segmentation, and feature extraction, followed by the identification of areas that were useful for identifying caries, tooth fractures, cysts, tumors, root canal length, and kid tooth growth. Furthermore, a number of studies have shown the value of dental imaging method analysis in biometrics, age estimation, and human identity applications. [7]

The goal of X-ray dental image analysis is to give dentists useful diagnostic data regarding their patients' oral health. Dentists can diagnose a variety of dental disorders, including cavities, periodontal disease, impacted teeth, irregularities in the bone, and misaligned jaws, by closely studying X-ray images of the teeth, jaws, and surrounding tissues.

**Detecting Dental Problems:** Dentists can detect hidden cavities or infections with the aid of X-ray analysis. These concerns may not be apparent during a clinical examination alone.

**Decide Treatment Needs:** Dentists can use X-ray images to decide the best course of action for each patient, including oral surgery, periodontal therapy, orthodontic treatment, and restorative procedures.

Examine Oral Health: X-ray pictures are helpful in tracking changes in oral diseases over time, enabling dentists to modify therapy as necessary.

Preventive Care: By using X-ray analysis, dentists can identify possible dental issues early on and take action to keep patients' mouths healthy and stop more troubles.

Patient Education: X-ray pictures are used by dentists to visually assist their patients in understanding dental issues, available treatments, and the value of good oral hygiene.

Academic and Educational Goals: Dental X-ray image analysis yields useful information for both teaching and academic research. Dentistry students can be taught practical knowledge about the anatomy, diseases, therapies, and diagnostic techniques of teeth through the use of this data in dentistry education. Dental students can improve their clinical abilities and get ready for real-world applications by analyzing X-ray pictures. Furthermore, these data aid in the development of new treatment approaches and discoveries in dental health for academic research. As a result, dental researchers and students benefit greatly from the analysis of dental X-ray pictures, which is important for both education and research.

The overall goal of X-ray dental image analysis is to assist dentists in giving their patients thorough oral care, precise diagnoses, and efficient treatment strategies.

### **1.2.5. Segmentation on the x-ray images**

The technique of breaking up a dental X-ray image into discrete and meaningful parts is known as "X-ray dental image segmentation." Teeth, bone, gums, and other anatomical elements may all be recognized and extracted from the image thanks to this segmentation technique. Accurately defining these structures is the main objective of segmentation in order to make additional analysis, measurement, and diagnosis easier.

Depending on the particular application and dental picture complexity, different segmentation approaches may be used. Thresholding, edge detection, region growth, and machine learning-based techniques are a few popular segmentation techniques.

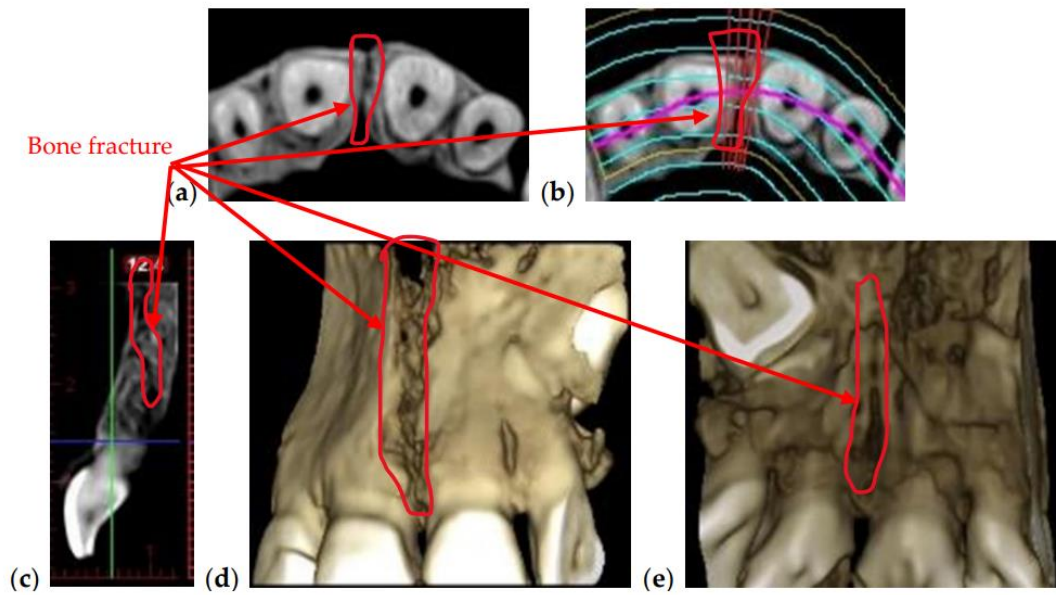
Thresholding: To differentiate between various image intensity levels, this technique entails setting a threshold value. One section is designated for pixels with intensity values above the threshold and another for pixels with values below it. Dental X-ray pictures are frequently segmented using thresholding to isolate teeth from surrounding tissues or the backdrop.

**Global Thresholding:** Selecting a single threshold value that makes a distinction between the foreground (items of interest) and background (unwanted elements) throughout the image is known as global thresholding. The histogram of the image's pixel intensities is usually used to determine the threshold value. It can be chosen by hand or automatically by applying algorithms like Otsu's technique. Pixels with intensity levels above the threshold are categorized as foreground when the threshold is applied, while those with values below are classed as background.

**Local Thresholding:** More adaptable than global thresholding, local thresholding—also referred to as adaptive thresholding—takes into consideration differences in intensity across various image regions. Local thresholding splits the image into smaller sections or patches and applies a different threshold to each region based on its unique local properties, as opposed to applying a single threshold to the entire image. This method is especially helpful for dental X-ray imaging, because tissue density differences and X-ray beam attenuation can cause fluctuations in lighting and contrast across different locations.

**Applications of Thresholding in Dental X-ray Images:** In intraoral and panoramic X-ray images, thresholding is frequently employed in dental radiography to separate teeth from surrounding tissues and the background. Teeth with greater intensity values can be extracted and analyzed more easily if they are isolated from the lower intensity background by applying the proper threshold. By separating dental anomalies from normal anatomical components according to changes in intensity, thresholding can also be used to segment dental malformations such as caries, fractures, or abnormalities in bone density.

**Challenges and Considerations:** The existence of noise, artifacts, and fluctuations in image quality, which might impact the segmentation accuracy, is one difficulty in thresholding dental X-ray images. It is critical to choose an ideal threshold value that minimizes pixel misclassification while efficiently separating the desired structures. Using automated threshold selection techniques or conducting experiments may be necessary for this. Despite being a somewhat easy and computationally efficient method, thresholding may not always yield satisfying results, particularly when dealing with complicated or overlapping structures.



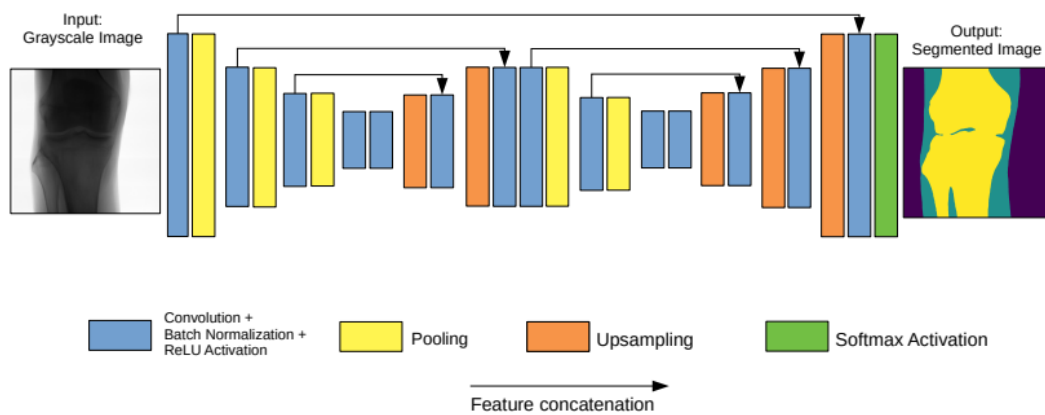
**Figure 1.2:** The 3D CBCT was utilized to examine a maxillary fracture from various perspectives. This analysis was previously described in the case of Patient V.L., a 29-year-old female diagnosed with a maxillary bone crack resulting from head trauma. [8]

Clinically and radiologically, patients must be examined for an accurate diagnosis. Panoramic radiographs are not necessary for density or postoperative examinations for bone diseases (including fractures or periodontitis) or for bone evaluation. A 3D CBCT with qualitative assessment and volumetric information should be carried out in such situations. **Figure 1.2** shows a CBCT examination that was performed for a maxilla fracture in our clinic.

### 1.3. Related Works

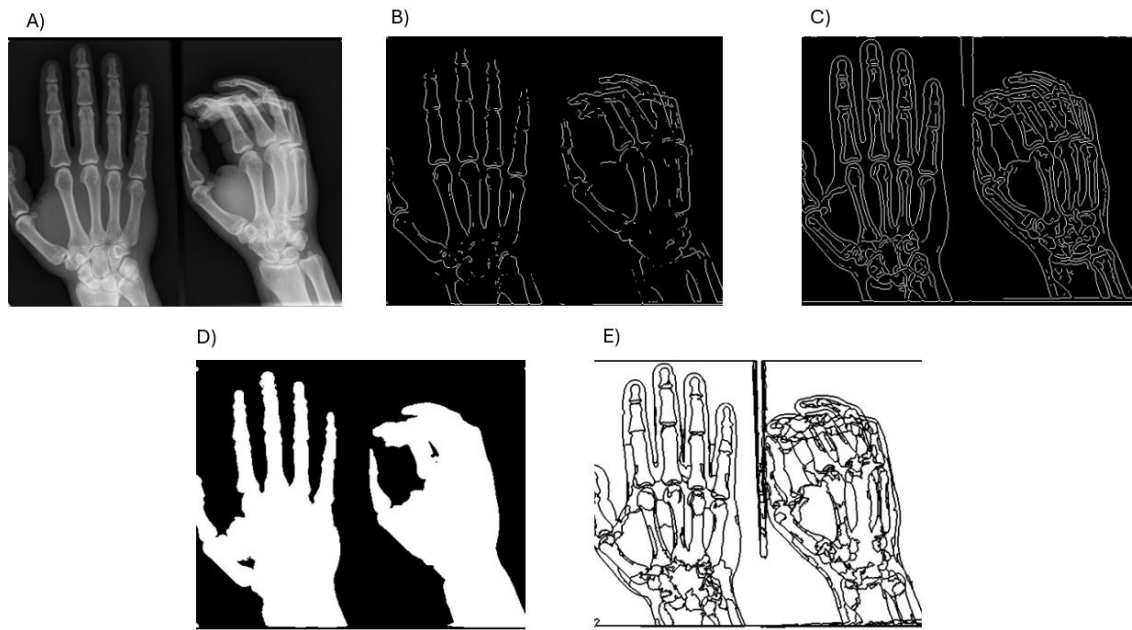
Ragodos et. al. 2022: This article highlights the importance of using deep neural networks (DNNs) for the detection of dental anomalies in children with orofacial clefts (OFC). Stating that the intraoral examination process currently used to diagnose these anomalies is costly and time-consuming, he argues that DNNs can increase efficiency by automating this process. The study detects 10 dental anomalies with a DNN model trained using intraoral photographs obtained from children around the world. He concludes that the model is faster than a dentist and performs similarly in most cases. It also allows dentists to provide post-hoc interpretation by using saliency maps to validate the model's predictions. [9]

Bullocak et. al. 2019: This paper presents a comprehensive solution that results in effective and reliable inferences by applying machine learning technique. With an overall accuracy of 92%, F1 score of 0.92, and AUC of 0.98, processing and identifying large numbers of X-Ray images required for neural network training, its applications outperform existing neural networks used for segmentation in non-medical scenarios. [10]



**Figure 1.3:** XNet architecture visualization with sample input image on the left and segmented mask output on the right. The preservation of fine-grained detail is aided by feature concatenation of same-dimension layers. The final pixel-by-pixel classification is provided by the Softmax activation function. [10]

Stoljescu-Crisan et. al. 2013: This paper's objective is to discuss the most significant picture segmentation techniques, beginning with a database made up of actual X-ray images. They go over each method's guiding idea and mathematical model, emphasizing its advantages and disadvantages. [11]



**Figure 1.4:** Figure displays an actual X-ray in **a**). Using Sobel to segment X-ray images, as seen in **b**). As seen in **c**), X-ray image segmentation utilizing a Canny edge detector. Using thresholding to split X-ray images in **d**). Segmenting X-ray images using the mean-shift technique see E. [11]

When the methods in **Figure 1.4** are compared, it can be said that the most efficient segmentation method is thresholding.

Lai et. al. 2008: Instead of using the outdated intensity or edge methods from earlier studies, the authors of this work suggest a novel method for automatically segmenting teeth based on texture features. Initially, a coarse clustering result is obtained by smoothing the teeth and enhancing the gum texture using image enhancement based on homogeneity assessment. The degrees of pixels that may belong to either section are then hypothesized using fuzzy inference. To get the entire shape of teeth, region growing based on inferences is the last step. The experimental findings demonstrate that, when it comes to segmenting entire teeth from X-ray dental pictures, their suggested strategy does, in fact, perform better than approaches that use direct intensity or edge. [12]

D. B. Prajapati et. al. 2012: In this study, they first extract individual teeth using a novel and straightforward CBIR technique, and then they extract geometric features from dental x-ray images for the purpose of human identification. They computed the distance vector for matching purposes by comparing the feature vectors from the database with the query image. To remove visual impulse noise, applied a median filter. [13]

Mahoor et. al. 2004: They offer an automated approach that uses Bayesian classification to categorize teeth in bitewing dental pictures. Based on a standard numbering system used in dentistry, each tooth is assigned an absolute number. The Bayesian classification of the molar and premolar tooth types in bitewing pictures is based on Fourier descriptors of their contours. Subsequently, in order to achieve very precise findings, the spatial relationship between the two types of teeth is taken into account when numbering each tooth and fixing the misclassification of some teeth. Experiments using 50 bitewing pictures with over 400 teeth demonstrate that our system can accurately categorize and provide an absolute index number to the teeth. [14]

Pushparaj et. al. 2012: The goal of this work is to develop a shape extraction and matching technique-based automatic person identification system. Teeth contour information is a good fit in this case out of all the features because it can offer better matching. There are four steps to this suggested procedure. Preprocessing is the initial stage. In the second, the top jaw, lower jaw, and individual teeth are segmented independently using integral intensity projection. The final stage used shape extraction using connected component labeling. For some misaligned photos, the outputs from the preceding stage are not up to par. Therefore, rapid linked component labeling improves it. Finding the Mahalanobis distance measure to compare dental records is the fourth step. [15]

Harandi et. al. 2011: In this article, a semi-automatic method is proposed to determine the root canal length in radiographic images based on morphological features. In this program, they have performed denoising, histogram equalization and frequency domain enhancement to improve dental radiographic images. Using morphological techniques, the pulp of the teeth is then extracted from a radiographic image. A collection of ideal dental radiographic images labeled by experts is used to test the proposed method. The practicality of the proposed algorithm is demonstrated by the generated results. [16]

Lin et. al. 2012: The method presented in this research is an automatic method for identifying gingival lesions in X-ray images of periapical teeth. The first step is the extraction of the tooth fragment, and the next step is the labeling and localization of the lesion areas. The first step includes morphological operations and histogram equalization to increase the difference between teeth and gingiva. Thresholding is used to distinguish between the two region categories. In the second step, the gingival fragments are first divided into normal, probable lesion or lesion and stage severe lesion regions. [17]

Nuansanong et. al. 2014: In order to analyze the ratio of the gap area between teeth, this research suggests using data mining and image processing based on the Active Contour Model. In order to assess the treatment, the experiment also has a connection to medical knowledge. According to the data, the expert's judgment to take a tooth has a  $78 \pm 7\%$  margin of error, whereas the ratio of the gap area between teeth in an extraction case is  $20 \pm 5$ . When there is no tooth extraction, the ratio of the gap area between the teeth is  $40 \pm 4.5$ , and the expert opinion on tooth extraction is  $60 \pm 6\%$ . As a result, there will be more instances of tooth extraction if there is a little space between the permanent and deciduous teeth. [18]

Lin et. al. 2014: The method studied in this paper is a method for segmenting individual teeth in periapical radiographs. This method consists of four distinct steps, firstly adaptive power law transformation for local singularity analysis, then Hölder exponent for tooth drawing, and finally morphological operations for snake boundary tracking and tooth recognition. [19]

Rad et. al. 2015: In this study, a system which can do analyze dental x-ray pictures and diagnosing teeth with anomalies related to caries is established. Enhancement is used to raise the caliber of x-ray images, and the thresholding technique is used to make the images simpler. A feature map of the tooth surface for analysis and detection was created as a result of the segmentation technique's use of the integral projection technique. However, tests show that the suggested method accurately segments and finds cavities and achieves high accuracy and promising results. [20]

Purnama et. al. 2015: In this research, firstly segmentation (using an active shape model to determine the root canal area), then thinning (to determine the centerline of the root canal area) and finally preprocessing (using the contrast stretching method). Thanks to these studies, they were able to semi-automatically determine the root canal length in a dental X-ray image. [21]

Jain et. al. 2017: In this research, they use automated segmentation to try and objectively diagnose cysts in periapical pictures. They have perfectly contained characteristics like lines and edges by harnessing the internal and external energy of image forces. The catch area surrounding a component can be developed via scale space continuation. [22]

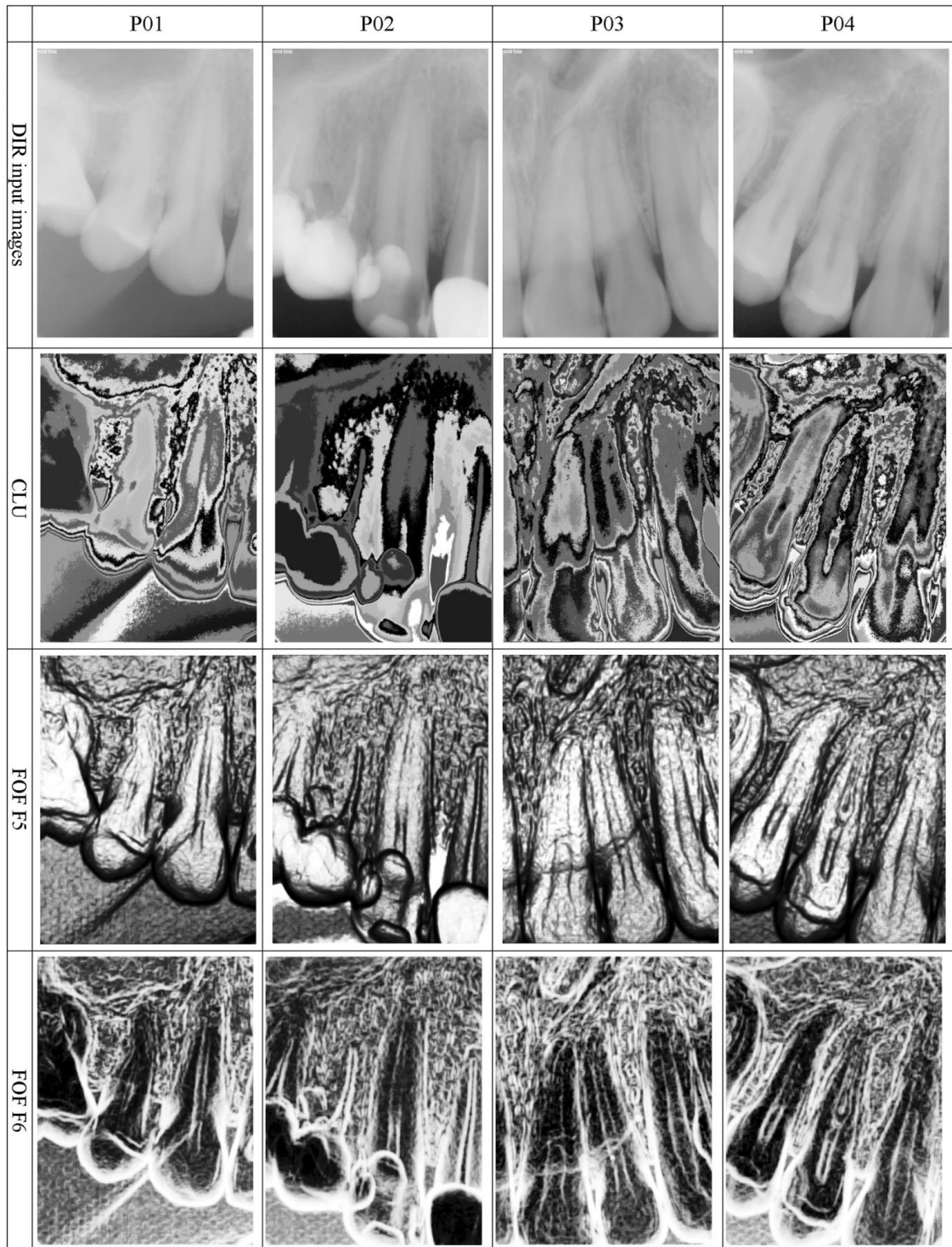
Singh et. al. 2018: By identifying regions of the tooth, such as the occlusal and approximal surfaces, where caries typically arises, artificial intelligence has been utilized to initially

diagnose the carious lesions. This method of identifying the carious lesions has made it possible to diagnose some other illnesses as well. They employed An unsharp marking filter is used to improve the high-frequency component and median filtering is utilized to reduce noise. [23]

Datta et. al. 2019: The goal of this work is to create a technology that will help dentists identify caries lesions more rapidly and precisely. This application is not a good fit for a deep learning-based approach since there is insufficient training data to adequately prepare the pre-trained model for deep learning. There are currently very few dental x-ray datasets accessible that show caries lesions. The approach is tested using the "Digital dental periapical x-ray database for caries screening" dataset. The suggested approach had an accuracy rate of 94% overall, and its average computation time was less than 4.5 seconds. [24]

Kumar et. al. 2019: Conventional image processing clustering techniques often overlook inaccuracies in determining the parameters and bounds of the dental sample. As more data is generated with the user, the clustering presentation is enhanced. Semi-supervised fuzzy clustering is a novel collective approach in DXRI segmentation. To reduce error, pre-processing of the input X-ray image is first carried out. Otsu's approach specifically divides the dental X-ray image into sections that are in the front and background. In this case, the FCM that was selected to divide the tooth regions started in the earlier stages. It is preferred to use a semi-supervised HTGkFCM in order to achieve a more optimal result than using standard approaches. [25]

Obuchowicz et. al. 2018: The purpose of this study was to assess how well texture feature maps identified discrete demineralization associated with the development of caries plaque. [26]



**Figure 1.5:** Defined images of caries-affected areas with sharp boundaries using the CLU, FOF F5, FOF F6 method. [26]

Rad et. al. 2013: They describe a technique in this study for segmenting and extracting features from dental x-ray pictures. The suggested approach has been put into practice by segmenting images using the level-set method after image enhancement and by illuminating tooth contours to finish the segmentation process. Furthermore, we used

texture statistical techniques using gray-level co-occurrence matrix to extract numerous characteristics from dental x-ray pictures. For automated dental systems, such as those for human identification or dental diagnosis, extracted data can be used to measure teeth. The significance of the suggested technique for extracting teeth from an x-ray image is demonstrated by preparatory experiments. [27]

Oliveira et. al. 2018: In this study, a comprehensive analysis of the literature on segmentation techniques used in dental imaging was conducted and it was concluded that threshold-based segmentation techniques received the most attention in the literature (54%). The types of X-ray images used, dataset characteristics and segmentation method were taken into account when classifying the ten segmentation methods studied and evaluated in state-of-the-art studies. Eighty percent of the evaluated articles used intraoral X-ray images in their experiments, indicating that they preferred to perform segmentation on images of previously isolated dental components rather than extraoral X-rays showing the bones of the face and the dentition of the mouth. [28]

Vijayakumari et. al. 2012: This work focuses on an automatic analysis of cyst using texture information to help the dentist with this process. There are three components to this work. Performance analysis of preprocessing for different cyst photos is covered in the first part. The gray level co-occurrence matrix for each cyst pattern is extracted in the second part. The final component uses the textural features to analyze various cyst patterns. [29]

Razali et. al. 2014: Estimating the age of unidentified bodies is the goal of the dental age assessment. The examiner currently completes the task by hand. The procedure might be changed to an automated one. The segmentation procedure, which splits an image into several useful sections depending on region and edge, was necessary for the construction of an automated dental age evaluation. Based on the connections found, the edge segmentation creates a contour. Two kinds of edge segmentation techniques Sobel and Canny are shown by the authors. A comparative analysis of the two approaches is the study's goal. The Sobel approach was able to segment every tooth area and eliminate noise from the x-ray image, whereas the Canny algorithm was unable to do so, particularly with regard to the incisors. The segmentation zone is significant since the Demirjian approach requires evaluating every type of tooth in quadrants two and three. The experiment's outcome shown that the Sobel algorithm could segment the majority of the teeth region in quadrants 2 and 3. [30]

Farzana Shahar Banu et. al. 2014: The automatic classification of dental cysts is the aim of this work. The region of interest is extracted using the contrast stretching technique and image negation. Texture characteristics based on gray level co-occurrence matrices are used for classification. It is determined that the centroid and K-means classifier classification results in feature space are promising. The results of this study will help the dental surgeon diagnose dental cysts accurately and arrange appropriate therapy. [31]

Amer et. al. 2015: The method for automatically extracting wisdom teeth from panoramic photos is presented in this study. It consists of three stages: first preprocessing, then ROI extraction and finally processing. The suggested method's results demonstrate that it is capable of extracting wisdom teeth successfully. The segmented images can then be used in a classification system to determine whether or not the extracted teeth are wisdom teeth, and to further categorize the wisdom teeth based on a particular issue, such as impaction. [32]

Poonsri et. al. 2016: They present a technique in this work for segmenting teeth from a panoramic dental x-ray picture. Three processes make up the suggested method: segmenting the teeth areas, matching templates, and identifying the tooth areas. First, the Mahalanobis distance method and Otsu's threshold are employed to locate the tooth area. Secondly, x-ray images of teeth are matched with teeth template images of varying image sizes. Lastly, a teeth section is created by matching the overlap area of numerous templates. Twenty-five dental photos are utilized to evaluate the effectiveness of the suggested strategy. There are 250 double-rooted teeth and 450 single-rooted teeth overall. For single-root teeth, the accuracy is 42.20 percent, while for double-root teeth, it is 49.04 percent. For single-root teeth, the accuracy is 42.20 percent, while for double-root teeth, it is 49.04 percent. There is still room for improvement in accuracy. Nonetheless, this is the first completely automated method for segmenting teeth using a panoramic dental x-ray image. [33]

Divya et. al. 2016: In this paper, an active contour model-based greedy segmentation technique is described. In order to analyze the characteristics of cysts, which are quiet initiative for panoramic photos, this method depends on a variety of image processing algorithms. For photos with noisy backgrounds or non-homogenous backgrounds, the techniques yield good segmentation results. The active contour model helps the snake to converge for the correct cyst extraction by utilizing the energy minimization function and the image parameters. After the entire segmentation procedure, the region removed can

help with cyst research by helping to categorize the various types of cysts and, consequently, aid in the treatment of jaw cysts based on their location and shape. The distinct contour that was retrieved for the cyst also aids in a better comprehension of the characteristics of cysts, enabling one to identify their behavior and prevent future growth. The various kinds of jawbone cysts can be categorized by analyzing the shape parameters that were derived using active contour. [34]

Zak et. al. 2017: This work suggests a technique for the initial stage of teeth segmentation, which involves choosing a region of interest that encompasses all of the teeth in the pantomograph. The suggested technique uses the pantomograph's energy, entropy, Hölder exponent, adaptive power-law transformation, and teeth line the line that separates the upper and lower jaws to identify the region that contains all of the teeth. Of those, 81.9% properly identify the teeth region and 34.0% accurately identify the teeth line. The method is the first stage in segmenting a single tooth, evaluating the dentition based on the presence of significant dental procedures, and automatically creating a patient's dental score. [35]

Alsmadi et. al. 2018: Using the same dataset from that work, they compare the Fuzzy C-Means clustering algorithm (FCM) and the New Clustering Approach (NFCM). Every evaluation parameter utilizing the complete database shows that the suggested NFCM performed significantly better on average than the FCM. Additionally, the P-value for every statistic was calculated. According to statistics, the observed difference is considered "significant" if the P-value is less than 0.05 and "highly significant" if it is less than 0.01. The examination of the FCM and NFCM results in a P-value for all evaluation measures that is less than 0.005, indicating that the observed difference is "highly significant" according to statistical standards. The increased TP value (from 83% to 90%) indicates that, in comparison to FCM, NFCM covers a larger lesion zone. When compared to FCM, the value of FP reduced from 9.1% to 6.1%, indicating that NFCM was successful in identifying the non-lesion locations. [36]

Divya et. al. 2018: The results of a comprehensive review of image segmentation algorithms used under radiologists' supervision on dental X-ray pictures are presented in this research. In contrast to panoramic images, a general comparison of segmentation methods has been explored for the segmentation of lesions and cysts. In order to analyze the different properties of the cystic region and to segment the required region of cysts, thresholding watershed and level sets approaches were selected. When it comes to

segmenting tumors and cysts, level sets segmentation yields superior outcomes. It is possible that the shape descriptors identified for the cystic region might be employed as feature vectors in image classification, allowing classifiers to automatically identify tumors or aberrant tissues from OPG pictures, aiding in their diagnosis and treatment. [37]

Son et. al. 2018: The Dental Diagnosis System (DDS), a revolutionary framework for using X-ray images to diagnose dental problems, is introduced in this paper. It includes a novel graph-based clustering technique for classification, semi-supervised fuzzy clustering for image segmentation, and a special decision-making process to identify the underlying ailment. When DDS was tested on 87 dental photos at Hanoi Medical University, it outperformed other techniques and had a high accuracy of 92.74%, demonstrating its usefulness in helping physicians make accurate diagnoses. [38]

Alsmadi 2022: The goal of this research is to improve the application of artificial intelligence in dental healthcare by presenting the Tufts Dental Database, a unique collection of 1000 labeled panoramic dental radiography images. This multimodal dataset comprises thorough classifications based on anatomical features and anomalies, together with unique aspects such as eye-tracking data and radiologists' think-aloud techniques. The dataset is analyzed using convolutional neural networks, which have shown excellent accuracy in the analysis of dental X-ray pictures. By offering a standard for improving and segmenting images and by simplifying the process of integrating human experience into AI systems, this dataset seeks to improve AI-powered anomaly diagnosis and classification in dental radiographs. [39]

Samiappan et. al. 2023: This study presents a novel technique for automated tooth recognition and dental disease classification using panoramic dental radiography, with the goal of improving the accuracy of medical diagnosis. The importance of panoramic X-rays in detecting anomalies in the buccal cavity and other oral regions that can go unnoticed is emphasized. The efficacy of the methodology is evaluated using precision, recall, F1-score, and accuracy measures; the results demonstrate the method's superiority over other currently employed methodologies. This research highlights the use of deep convolutional neural networks in enhancing the diagnostic capabilities of dentistry. [40]

Kim et. al. 2020: This study presents a semi-automated technique for detecting dental cavities in digital X-ray pictures using superpixel segmentation, which is essential for

dentists to diagnose and detect dental cavities early. By dividing an image into homogeneous parts, superpixel segmentation improves detection. To eliminate numerical mistakes associated with common approaches such as the active contour model and standard DRLSE, and to improve accuracy, the suggested method integrates superpixel techniques with DRLSE. Through comparisons utilizing 11 real teeth samples, the efficacy of this new methodology was shown. It outperformed the other methods in terms of classification accuracy and error metrics. [41]

Devi et. al. 2018: This work addresses the problem of segmenting cysts in dental X-rays, which are difficult to segment because they frequently have uneven exposure and poor contrast, which makes segmentation techniques laborious. The fast marching method (FMM) and circularly symmetric isophote characteristics are combined in a newly designed hybrid automated technique. The method finds the Maximum IsoCenter (MIC) as the seed point for the model-based segmentation by using isophote curvature. Similar to Dijkstra's method, the FMM effectively defines the boundaries of the cystic region. With an average execution time of 2.8 seconds and a 95% segmentation accuracy, our two-stage method demonstrated robustness and a strong correlation with human methods. This method could lead to better patient care and increase the possibility of using automated methods to diagnose dental disorders. [42]

Shubhangi et. al. 2022: According to this study, the automatic tooth detection and dental status categorization system created with the aid of comprehensive x-ray pictures can assist medical professionals make more accurate diagnostic decisions. Panoramic radiographs from three dental clinics were gathered and analyzed for the study, which identified fourteen probable dental issues. CNNs were trained on an annotated dataset in order to extract data on semantic segmentation. The bounding boxes corresponding to dental abnormalities were then segmented and fine-tuned using a variety of image processing techniques. The last stage involved labeling every tooth sample in the designated area of interest and using majority vote based on a histogram to determine which concerns were impacted. [43]

Prajapati et. al. 2021: This article looks at how different dental x-ray imaging techniques are analyzed to find abnormalities, changes in tooth structure, or dental issues. There have been rumors that dental imaging has potential use in biometrics. It has been highlighted that the unclear and irregular shapes of different teeth make human dental picture analysis a challenging and time-consuming operation. As such, physical assessment of dental

anomalies requires outstanding attention. However, it has been said that automation is required in the field of dental picture segmentation and analysis to offer improved treatment planning and error-free diagnosis. [44]

Ali et. al. 2016: The significance of software metrics in the software business is emphasized in this article. These metrics offer measurements that are essential for managing software processes and products, including software quality, complexity, maintainability, and size. It is possible to determine whether the project is within expected standards or whether there is a departure by measuring the software. The ideal limits and ranges of these measurements would be determined by thresholds or reference values, which are frequently absent from the metrics presented in many publications. [45]

Muresan et. al. 2020: This article emphasizes how the remarkable results that deep convolutional neural networks (CNNs) produce in detection, prediction, and classification have made them extremely popular in medical research. Specialists can identify issues in the oral cavity or difficult-to-reach regions with the use of panoramic dental radiograph analysis. However, a low-quality imaging or weariness could lead to a different diagnosis, which would make therapy more difficult.

This article proposes a novel method for classifying dental problems and automatically detecting teeth using panoramic X-ray pictures. Medical professionals can use this method to determine the accurate diagnosis. Panoramic radiographs obtained from three dental clinics were anodized and 14 potential dental issues were highlighted for this reason. Using anodized data, a CNN was trained to extract semantic segmentation information. [46]

Al-Ghamdi Asa et. al. 2022: According to this article, analyzing dental radiographs is a crucial step in the diagnostic process in regular clinical practice. During the diagnosing procedure, the dentist must interpret various dental issues, tooth counts, and associated illnesses. This paper proposes a convolutional neural network (CNN) for panoramic radiographs that divides dental radiographs into three categories (implants, fillings, and cavities). A variant of the NASNet model with varying numbers of maximum pooling layers, dropout layers, and activation functions is employed in this research. The data will first undergo preprocessing and augmentation. A multi-output model will then be built. The model will then be assembled and trained, and the accuracy and loss curves will be

the assessment parameters used to examine the model. The model outperformed other existing algorithms and reached an accuracy of over 96%. [47]

Almalki Ye et. al. 2022: According to this article, teeth are among the hardest elements in the human body to work with. It has been stated that the inefficiencies, complexity of the experimental process, and high level of user intervention associated with current dental problem detection techniques. Earlier methods for identifying oral diseases required a dentist to assess and inspect the condition, and they were laborious and manual. A novel method based on a deep learning model is suggested to detect and categorize four frequent dental concerns (caries, root canal treatments, dental crowns, and collapsed root canal treatments) in order to solve these problems.

Using the deep learning model YOLOv3, an automatic tool was created in this study that can identify and categorize dental anomalies, such as dental panoramic x-ray images (OPG). A Dental X-rays dataset was developed to identify and categorize dental problems since there were insufficient datasets available. 1200 photos make up the size of the dataset that was employed following the augmentation process. The collection is made up of panoramic dental pictures that show dental conditions such dental crowns, collapsed root canal treatments (BDR), caries, and root canal procedures. There are 30% of test photos and 70% of training images in the data set. Test photos were used to assess the YOLOv3 model after it had been trained. According to experiments, the suggested model performs better than the best current models in terms of accuracy and universality, achieving 99.33% accuracy. [48]

Geetha et. al. 2019: This article suggests an appropriate textural property for using digital radiography to diagnose dental caries. The dental diagnostic system uses morphological operations and adaptive thresholding for segmentation, a Laplace filter for image sharpening, and a support vector machine (SVM) for classification. The segmented image is processed to recover its texture properties, which are then fed into the classifier to determine if the image is normal or rotting. The findings of the experiment indicate that when compared to other textural feature types, the GLCM (Gray Level Co-Occurrence Matrix) and GLDM (Gray Level Difference Method) textural features offer superior performance assessments. 96.88% accuracy, sensitivity (1), specificity (0.8667), and precision (96.08%) were attained. Analysis of Variance (ANOVA) was used to evaluate the data at the 5% significant level. This outcome demonstrates the considerable impact feature extraction techniques have on performance metrics. [49]

Lakshmi et. al. 2020: According to this article, eating habits and overindulgence in chocolate are to blame for the rise in dental disorders in modern times. It is highlighted that a prediction model that can identify oral disorders at an early stage needs to be created. Accurate early dental disease detection is facilitated by dental image processing. Research on the segmentation of dental x-ray images is crucial for the diagnosis of dental disorders. The suggested methodology uses an adaptive pre-processing technique to balance dental image contrast and brightness. Graph cut segmentation was then applied to separate the dental x-ray pictures' foreground and background. To anticipate dental pictures, a Deep Convolutional Neural Network (Deep CNN) was employed. An analysis and comparison are conducted between various segmentation approaches, including Canny Edge Detection, Watershed, Threshold, Active Contour, Sobel, and Otsu's Thresholding Method. Graph cut segmentation and Deep CNN together produced a 98% accurate approach.[50]

Rajee et. al. 2021: According to this article, human teeth are hardy and frequently endure into death. As a result, teeth are crucial in the forensic department's identification of a deceased or missing person. Another crucial step in the forensic investigation process is gender discrimination. Further study is still needed, nevertheless, to create an autonomous tooth gender prediction system based on deep learning algorithms.

An method to predict human gender from dental x-ray images (DXI) is proposed in this research. Three steps make up the algorithm: segmentation, gender classification, and preprocessing. To eliminate undesired noise, such as Gaussian, speckle, and impulse, the initial stage involves denoising DXI using a prime magic square filter. The denoised DXI is segmented in the second stage using gradient-based iterative thresholding segmentation. [51]

Liu et. al. 2022: According to this article, digital dental x-ray pictures are a crucial starting point for the diagnosis of oral health conditions, particularly endodontic and periodontal conditions. Conventional diagnostic techniques are more subjective and require more energy than alternative procedures since they rely on the expertise of medical professionals. Low accuracy and poor lesion classification define current computer-aided interpreting technology. This study suggests utilizing a convolutional neural network (CNN) to effectively and accurately identify frequent lesions in digital dental x-ray pictures. Dentists from Shandong University's Qilu Hospital gathered and added to a total of 188 digital dental

X-ray photos that were identified as having periapical periodontitis, tooth decay, periapical cysts, and other prevalent dental disorders for the study. Four CNN models were trained with images and labels such as :VGG-16, InceptionV3, ResNet-50 and DenseNet-121.

The trained DenseNet-121 network model achieved 99.5% classification accuracy, compared to the test set's four trained network models' average of 95.9%. This indicates that when applied to interpret digital dental x-ray pictures, CNNs are a quick and accurate way to diagnose auxiliary dental problems. [52]

Raju et. al. 2011: The suggested algorithm in this article uses a variety of features, including energy, contrast, homogeneity, and correlation from the Gray Level Co-occurrence Matrix (GLCM) to characterize the texture of the extracted tooth and Fourier Descriptors for shape analysis. As a result, this algorithm looked at the extracted tooth's shape and texture analysis as characteristics. The query and database images were then compared using the mean square error. It was discovered that 40% of the true images in the top 5 fetch lists of a database with 25 images were real. But when two photos have identical texture and shape properties, the algorithm breaks. In the future, research will focus on developing a novel feature extraction method that investigates the individual differences in tooth geometry.[53]

Mualla et. al. 2020: This article describes how estimating chronological age from panoramic dental x-ray pictures is a crucial forensic science task. Numerous statistical methods that take into account the teeth and jawbone have been proposed. Further study is necessary to create an automatic dental age prediction system based on machine learning techniques. This article suggests a transfer learning-based automatic dental age estimation technique.

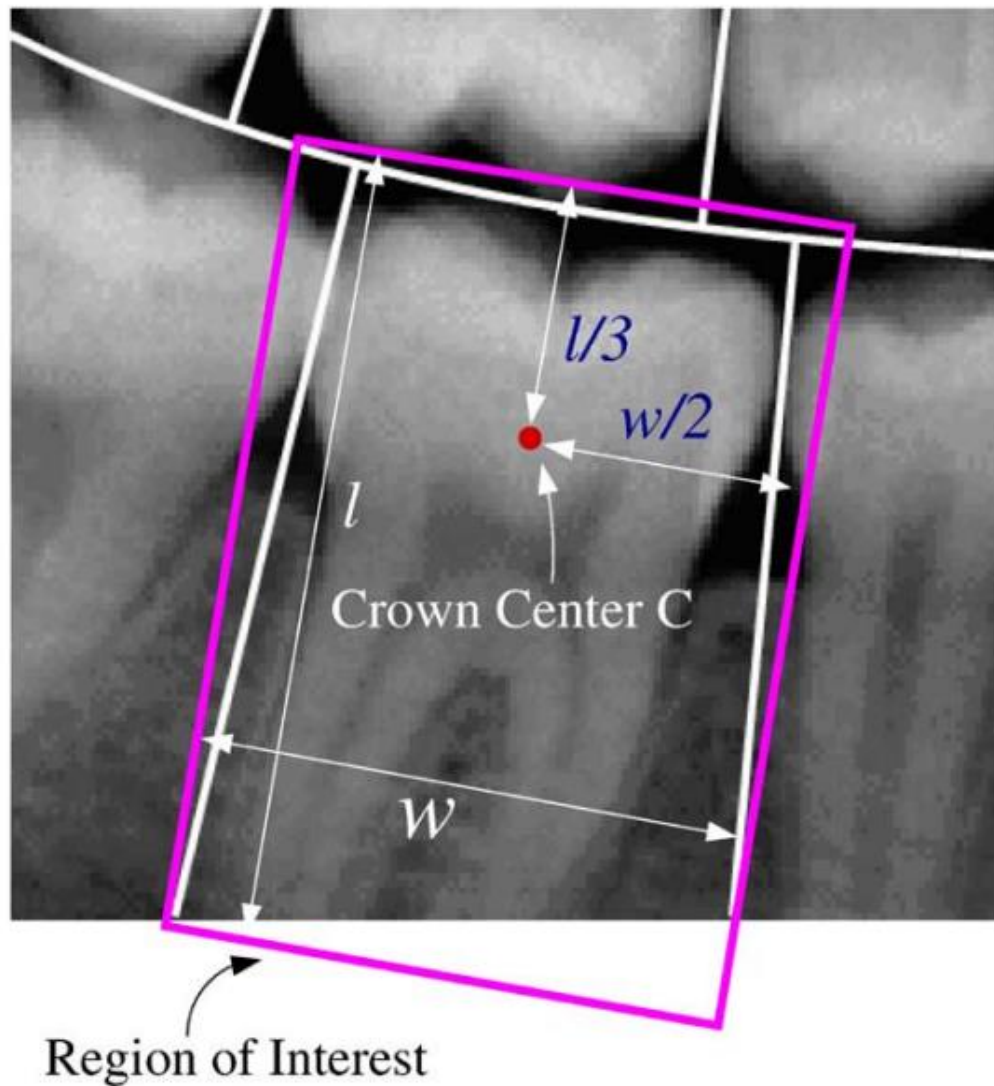
AlexNet and ResNet are used in the suggested strategy to retrieve features. A number of classifiers, such as decision trees, support vector machines, k-nearest neighbors, and linear discriminators, have been suggested to complete the classification task. The suggested method was assessed using a set of suitable performance criteria on a dataset of 1429 dental x-ray pictures. The collected results indicate that the performance of the proposed technique is promising. [54]

Anil et al. 2004: This article suggests a novel semi-automated technique for human identification using dental x-rays. Three steps make up this method: matching dental

features, extracting dental features, and segmenting x-rays. The tooth shapes are the feature that's being employed here. The distribution of background and tooth pixels is described in the first stage using a probabilistic model. Following the extraction of the tooth contours, a transformation is used in the second stage to address geometric changes in the image, and a matching distance is computed. These matching distances are used to make the ultimate decision in the last stage.

On a limited database, preliminary studies demonstrate the viability of this strategy. The approach is limited, nevertheless, if there are large angle changes between the AM (pre-mortem) and PM (post-mortem) photos, if the images are extremely fuzzy, if the query shape is partially veiled and there is insufficient information, or if some teeth have been extracted. Additional data, such as artificial tooth prosthesis, trabecular patterns, and striae (linear patterns), can be used to answer these issues.

Future studies aim to increase the reliability of identification by using additional sources of information. Additionally, when there is more than one PM image of a person, efforts are being made to provide better recall by combining the results obtained from these images. It is planned to develop an image enhancement algorithm to process low-quality x-ray images and evaluate the algorithm on a larger dental x-ray database. This study aims to develop more effective and reliable methods for human identification based on dental x-rays.[55]



**Figure 1.6:** The generation of ROI and the crown center. [55]

For each tooth in **Figure 1.6**, a rectangle that closely encloses the segmented area is constructed based on the segmentation output. The term ROI (Region of Interest) refers to this rectangle. Crown Center, or C, is the point inside this rectangle that is selected to be used in the shape extraction process. Point C is located one-third the length of the ROI from the top of the rectangle, and it is equally spaced from the other two edges.

This approach aims to determine a central reference point for tooth shape extraction, and these points are located within the rectangle obtained during the segmentation process. This provides a consistent and standard reference point for analysis and comparison of teeth.[55]

Morais et. al. 2015: This article describes how difficult and time-consuming it is to detect dental implants in patients who do not have records. In the conventional approach,

professionals check the 2D x-ray image with a public database; this procedure is entirely user-dependent. Implant model detection requires automatic/semi-automatic frameworks because of the enormous number of implants and their similarities.

This study proposes a novel computer-aided framework for dental implant recognition. The suggested technique is predicated on ideas from image processing: a machine learning strategy for implant pattern detection and a segmentation strategy for semi-automatic implant drawing. While the segmentation technique is the primary focus of this work, early information about the machine learning approach is also provided.[56]

Rad et. al. 2013: The significance of dental x-ray image analysis for the quantitative advancement of medical imaging systems is emphasized in this article. This article presents a method for segmenting and extracting characteristics from dental x-ray images. The suggested approach was put into practice by defining the tooth outlines to finish the segmentation step and applying the level-set method for segmentation following picture enhancement. Furthermore, utilizing gray level co-occurrence matrix (GLCM) and textural statistical approaches, certain features from dental x-ray images were retrieved. [57]

#### **1.4. Overview Of The Proposed Solution**

This work specifically dealt with deep learning and machine learning approaches for nearly all the segmentation and classification aspects of dental X-ray images in the present project. The implementation is based on incorporating and comparing several core deep learning frameworks like TensorFlow and PyTorch and segmentation models using `segmentation_models_pytorch`, which is designed to apply segmentations to medical images. This library is made of models such as the UNet, FPN, and PSPNet, which have been trained on a large size of data. In interfacing the data collection for preparation, Google Drive was incorporated to aid in easy download of large datasets obtained from the compressed file, and then enhance data processing. The annotations were obtained from the CSV file and loaded into a PyTorch pandas data frame and unloaded the images and annotations by creating a dataset class. Image preprocessing to enhance the quality of the images and prepare them to input into the neural network included data augmentation and transformations.

Segmentation indeed forms part and parcel of any image processing technique especially in locating regions of interest (ROI) common in dental X-ray images. It employed existing models from the `segmentation_models_pytorch` to segment structures in dental images with preciseness; UNet, FPN as well as PSPNet. It is done through using the Loss function of Dice and the Adam optimization of model weights. Following segmentation graphs of features were computed in the subsequent process and employed for classification. Segmentation model was used for feature extraction and the encoder part of the segmentation model was used to do this.

For classification in this research, different channels of classifiers including Decision Tree, k-Nearest Neighbors (k-NN), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM) were applied. These classifiers successfully classified dental conditions with intents identified from the segment features. It is worth noting that various measures were used to determine the performance of the developed model. For segmentation the proposed approach uses the Dice coefficient, Mean Absolute Distance (MAD) and Hausdorff Distance. In the classification, the accuracy and the confusion matrix were adopted as the assessment criteria of the model.

Image segmentation results were visualized with the Matplotlib toolkit, hence an appreciation of the comparison between the generated segmentation masks with the original images could be made more easily. The proposed visions of the project are to enhance the visualization accuracy and speed of diagnoses in dental structures. The future development direction includes further optimization of the algorithm to achieve better segmentation and incorporating more neural network algorithms with improved accuracy to deal with other dental pathologies and achieve better system performance. This approach is general, and the goal is ambitious, but such an idea is expected to be innovative to support dentists in diagnostic activities as well as enhance patient care.

### **1.5. Objectives and Contributions Of The Thesis**

The main goal of this project is to automate and improve the analysis of dental x-ray images using artificial intelligence (AI) and machine learning (ML) techniques. We aim to develop a system that will significantly assist dentists in the diagnosis and treatment processes, provide data for educational purposes and increase efficiency in healthcare services. Within the scope of the project, it is aimed to provide an AI-based solution that

performs segmentation and classification operations on dental X-ray images and provides high accuracy and speed.

The development of automatic segmentation and classification algorithms will be possible by detecting the regions of interest in dental X-ray images and classifying these regions according to dental diseases. Additionally, improving the doctor and patient interface will enable doctors and patients to easily access the system by creating a user-friendly platform. Thanks to this interface, doctors will be able to make diagnosis and treatment plans more quickly and effectively.

The project also aims to create accurate and detailed labeled dental x-ray data sets that can be used for educational purposes in dental faculties. This data will improve the quality of education by enabling students to work on real-world cases. Another important goal of the project is to reduce misdiagnosis rates by minimizing human error with automatic analysis systems. In this way, patients will be protected from unnecessary or incorrect treatments.

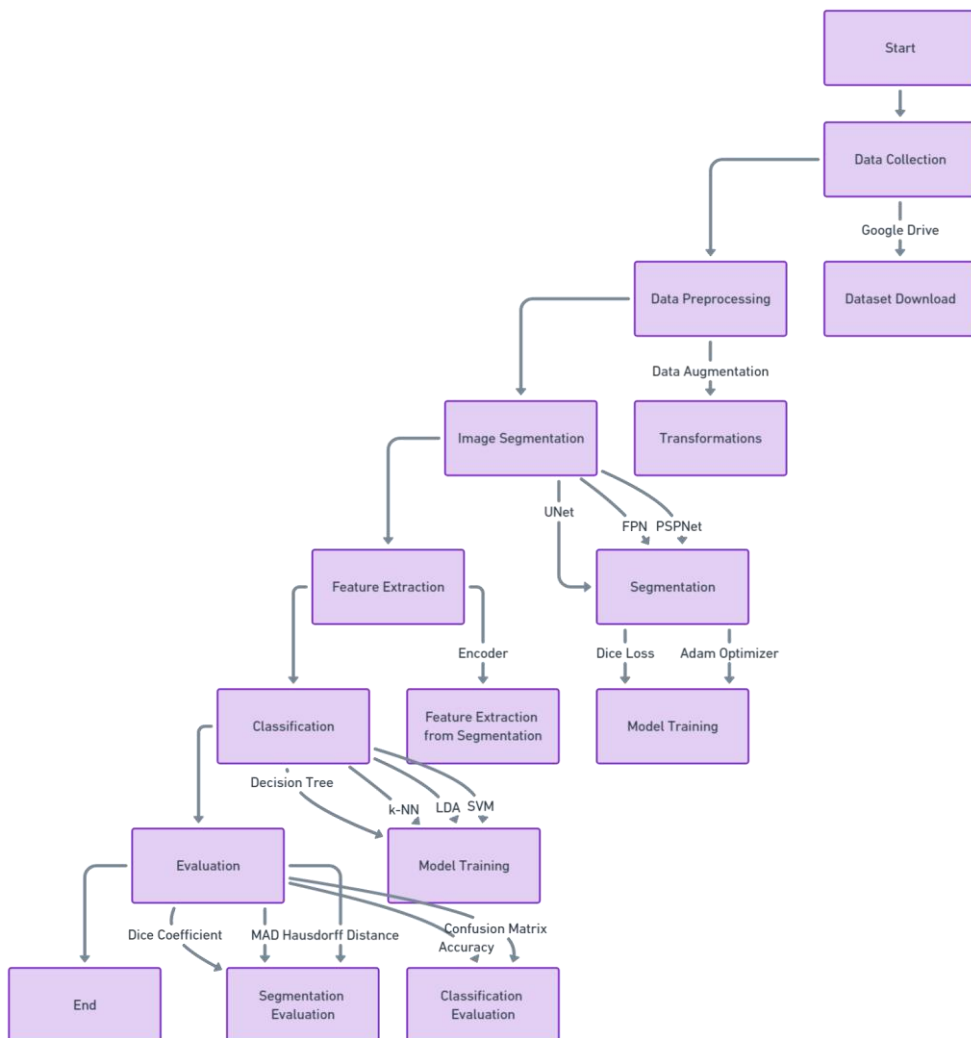
In addition, archiving digital x-ray images in a central system will eliminate the need to re-take x-ray images if patients visit different doctors. This will increase continuity and efficiency in healthcare by providing quick access to patient information.

The outputs of the project include the development of high-accuracy diagnostic systems, the provision of detailed and accurately labeled data sets that can be used in education for dental faculties, and the development of a user-friendly interface for doctors and patients. This project aims to provide significant improvements in diagnosis and treatment processes and improve the quality of patient care by increasing efficiency in healthcare services by providing innovative AI solutions in dentistry.

## CHAPTER 2

### 2. THEORETICAL PART

#### 2.1. Components Of The Developed Methodology



**Figure 2.1:** Components of the developed methodology

The method plan we followed in this project is shown in detail as a diagram in **Figure 2.1**. Our artificial intelligence-based prediction model project, which we created using X-ray images, first started with the preparation of the process data set. Ethics committee rules were followed when creating the data set, this step was an important step because we used human medical data. In this regard, extensive research was carried out to find public data. After an extensive data collection process, the preliminary preparation and data preprocessing phase for the model of this data began. At this stage, the data was standardized by Resizing, Color Conversions, Rotation, Flipping, Translation, Scaling and Adding Noise. Then, the data was labeled. After this step, we moved on to the image segmentation step. In this step, various applications were first tried, segmentation algorithms such as UNet, FPN (Feature Pyramid Network) and PSPNet (Pyramid Scene Parsing Network) were studied. Finally, the decision was made on UNet and segmentation was carried out with the UNet algorithm. Then, in the classification phase, the extracted features are classified using simple and interpretable models such as Decision Tree. Features obtained from the segmentation phase are reprocessed for more complex classification tasks and classification models are trained using machine learning algorithms such as ,R-CNN , k-NN, LDA and SVM.Finally, the decision was made on faster R-CNN was carried out.The performance of the trained models was evaluated with metrics such as Confusion Matrix and Accuracy.

## **2.2. Dataset**

Datasets are one of the most important and first steps that any artificial intelligence project needs to come up with today. Creating the correct dataset is the part that needs to be calculated and adjusted before starting a project. The right data set should be purposeful and the more data there is, the better it can be tested. For this reason, one of the parts where we spent the most effort in our project was creating the data set. Especially in the medical field, obtaining high quality and reliable data sets for use in dental x-ray image analysis is a challenging process. In this project, care was taken to use the best approach and an adaptable method in data collection setup. First of all, different data sets were evaluated for usability in open source, and one of them was chosen because it gave a general data set and it was possible to generalize the model with such a set. These are typical situations in dental health and therefore can serve as a reference for the normal

population. It is important to note that open source data was used to obtain basic information about the model in the early stages of the project.

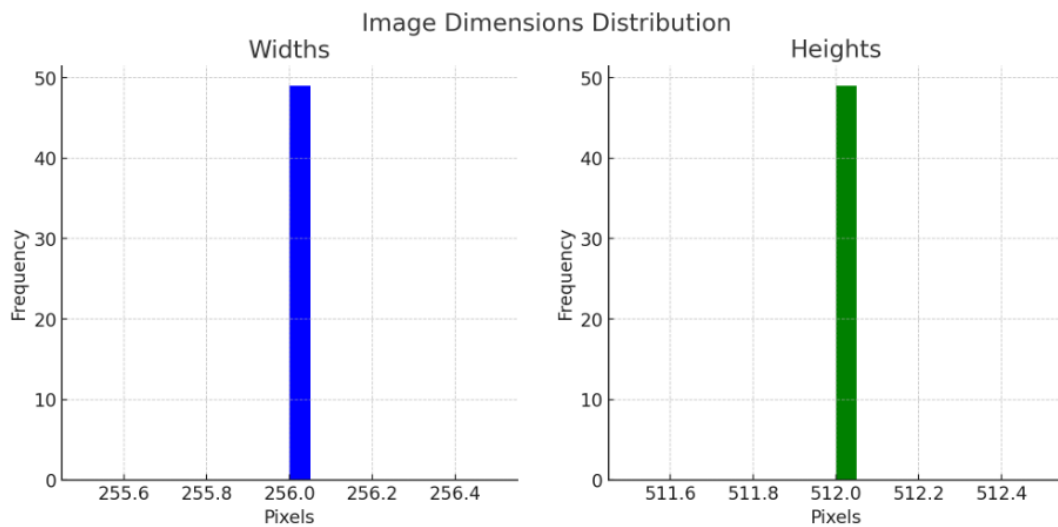
Patient demographic information in the study included patient characteristics while radiographic images of the patients' teeth were obtained. All the conditions of the images were standardized to crowd the pixel density, color depth, and contrast ratio of the image data. The images in the dataset were then preparatory by prep labeling each image to the pathology or condition the image depicts. The patients' information was protected throughout the data collection process and general ethical principles were adhered to; ethics committee clearances were sought for the study. Every information that was gathered for the sake of the project was stored on cloud and all the mentioned encryption methods were used to process such information – thus the strict approach was applied while working with such information.

The collected data includes age, gender, ethnicity, etc. It was later extended by images from dental scans of patients with different demographic characteristics, for example It was assumed that such expansion will enhance the model's greater sensitivity to patients' properties, including age, gender, or geographical location.

Thus, when adopting an organized approach to data gathering, the project can obtain several types of public data and non-public data that has been collected at different clinics, which would eventually enhance the use of the project in practical work. It not only made it more assured that the project will be done with full and proper adherence to ethical standards but it also enhanced the model's capacity for generalization.

It is important to note that working with image data for images within image processing projects, some preparations are needed to prepare these images for the proper transformation to the model.

In turn, it is required to illustrate how to make all those data standardize, augment, and perform an error analysis in order to improve generalization skills of the model despite the fact the results defined can be rather accurate. These are the critical steps needed in order to pass through all the phases of the project so as to have this model in order and working.



**Figure 2.2:** Image dimensions distribution

### 2.2.1. Data collection

It is one of the most important steps in creating the dataset. To collect accurate and purposeful data, various open source sources such as Kaggle were used. Since the data in this project consists of dental x-rays, care was taken to provide reliable and high quality data. To ensure that the data preparation process was effective, the image database of human teeth was expanded. In general, this dataset should include a variety of dental pathologies and the images should be from patients of all ages and backgrounds. Data collection is important and occurs in the early stages of the project and therefore has a great impact on the outcome of the project.

### 2.2.2. Data standardization and preprocessing

Data analytics is a discipline that has gained great importance in the business world today. However, the accuracy and reliability of data analytics results depend on a fundamental step called data preprocessing. Data Preprocessing is the process of cleaning, transforming and organizing the raw dataset.

Data preprocessing is a series of steps taken to make a data set analyzable. Raw data can often be complex, incomplete or inaccurate. Therefore, data preprocessing does some transformations on the raw data, making it more suitable for data analytics.

**Improving Data Quality:** Data preprocessing aims to improve data quality. Raw data sets may contain inaccurate or missing data. Thanks to data preprocessing steps, these errors are detected and corrected, missing data are completed and the data set is made consistent.

**Improving Data Analysis Performance:** Data preprocessing can speed up the data analysis process. Some transformations made on the raw data set enable analysis algorithms to work more efficiently. For example, removing redundant or repetitive data can shorten analysis time.

**Ensuring Accuracy and Reliability:** Data preprocessing increases the accuracy and reliability of results. Incomplete or incorrect data can lead to incorrect results. Thanks to data preprocessing steps, such errors are minimized and reliability is added to the analysis results.

As for all the gathered images, it was required to ensure that all the images in the slideshow were of high quality with proper resolution and the proper choice of colors and contrast. Namely, reference was made to the methods used to increase the contrast of an image depending on the histogram, edge detection, noise elimination. They give an impression of equalization of the gathered data and assist in the process of preparation of the data for training of the model.

### **2.2.3. Image augmentation**

To fix the problem of excessive training, data augmentation was incorporated to enhance the general performance of the model in the classifications. The images were processed through other operations including rotation by a random degree and either horizontally or vertically flipping the images followed by scaling and cropping of the images. This also assists the model to have more positive control of the simultaneous change of the pose, the angle, and the dimensions.

### **2.2.4. Image normalization and standardization**

The tested images have to be normalized and standardized so that pixel values of the respective images fall within an acceptable range of the set standard scale. These steps make learning easier and faster by the model since it can directly jump into the training process without a lot of hitches.

### **2.2.5. Data quality control and error analysis**

In order to eliminate all possible errors and deficiencies that could appear at one or another stage of the analysis and that may result in the manifestation of the certain discrepancies in the data set, the specific diagnostic test was conducted at each phase of the analysis. Error analysis also has its significant part to play in the model so that it does not mislearn and if it does; it will affect the rest of the entire model in the future.

### **2.3. Detailed Of The Proposed Method**

In the segmentation phase of this project, one aimed to determine and correctly separate areas of tooth and gums in the dental X-ray images. Before segmentation, some operations were taken on the images to improve image quality; these include normalization, filtering of noises and improving contrast. The segmentation task concerned the use of a segmentation algorithm, and this made it possible to demarcate these certain regions more effectively. This separation is important in ensuring that aspects of oral health status are well described and understood hence help dental specialists in making correct conclusions on variability particularly on diseases like gum diseases or forming a cavity. Also, the presented segmentation process creates opportunities for further development based on computer-aided image analysis and diagnosis in correspondence with the different spheres concerned with medical imaging. The model was trained extensively on a variety of data set, and after that was validated carefully to increase the ability to generalize and to prevent over-learning. In my opinion, the phase that has great importance in this study is the 'segmentation phase' precisely because it helps for evaluating the dental X-ray images as much as possible including both the tooth and gum regions definitely.

The process of classifying dental X-ray images was done with the help of a classification methodology. The goal of this process was to allow the model to familiarize itself with unique characteristics in these images and successfully identify different dental disorders. While performing data collection, the dataset of different types of dental pathologies and patients of various age and gender was used. The given dataset was also preprocessed, being as balanced as possible and making the model develop the aptitude to perform equally well in all situations.

The employment of Convolutional Neural Network (CNN) architecture was deliberate in that, during the learning phase, it provides for filtering out of relevant features. This

architecture is intended and aimed to bring success and proper result in image processing. The selected CNN architecture was used when in the training phase, the model was trained iteratively. Next, hyperparameters for each of the model were tuned and model was tested on test data set.

In order to examine the micro-level classification possibilities of the model, a Confusion Matrix was built. This matrix depicted how the model definitely classified and misconstrued various situations based on True Positives, True Negatives, False Positives, and False Negatives. These steps made it possible to identify strong and weak points of the model to further enhance it in the future. Thus, the classification methodology used in the project was revealed to be an effective approach to the proper categorization of the cases of dental X-ray images.

A major feature that can be inferred from this tool is that it is simple and friendly for users, these are the characteristics it has over other web frameworks: Fast Execution, it generates Automatic Documentation, it supports Type Checking, Async Support, and has the feature of Dependency Injection. And the created website had the HTML interface in order to simplify the analysis of the dental images for the dentists. Indeed, the proposed interface is aimed at enabling dentists to conveniently analyze the X-ray images of patients. Here are the key features and technical details of the interface: Here are the key features and technical details of the interface:

This aspect focuses on having an easy design of the interface and its goal of ensuring that the dentists using the interface would not have a hard time in using the interface and its functions in the right manner. The general usability, including a clean design and readily visible and clickable colours have been approached intentionally to facilitate the users' interaction.

The interface also has a part where the patient information and doctor information is displayed and inputted. This slot enables the dentist to enter fundamental demographic data like the patient's age, name, sex and other data. All these aspects are used in order to well assess analysis results. Furthermore, dentists can also create diagnoses through the logged in dentist's account.

Main windows of the interface have a harmonized design and contain a tab to analyze and classify the images made by dental X-ray. This tab is in fact convenient for dentists to

carry out classification tasks on the images and scrutinize the outcomes of the analysis meticulously.

The interface includes segmentation tools which help in possible partitioning of the teeth and gum areas in dental images. It gives the dentists an opportunity to thoroughly study tooth and gum tissues, diagnose certain pathologies, and develop a prognosis.

The interface offers a specifically designed reporting tab which offers the analysis of the reports along with segmentation stages. About the patient's condition, dentists can get elaborate paperwork from this section and incorporate it in formulating the treatment regimen.

Through this simulation, dentists ought to better control processes that analyse dental images, hence enhancing the efficiency of the patient treatment procedures. This includes a design that ensures it is easy to use while at the same time being replete with features that enhance the overall efficiency of an institution that deals with dental services.

## CHAPTER 3

### 3. EXPERIMENTAL PART

#### 3.1. The Test Environment

In this project, an effort was made to create a test environment that was most suitable for the purpose and would be most useful in real life. By conducting literature research, the methods used to test artificial intelligence models were investigated. And it was decided that the most suitable F1 vesaire testing methods with Python should be used.

The ability of classification models to correctly predict the label given input data is measured by accuracy. A balanced dataset, or nearly equal numbers of data points for each class, is required to utilize accuracy as a statistic for a classification model. Precision, recall, and F1 scores are taken into consideration if the data are not balanced.

**Precision:** Precision is a metric that quantifies how often a machine learning model correctly predicts the positive class. The precision is calculated by dividing the total number of samples predicted as positive (true positives) by the number of samples that the model properly predicted as positive (both true and false positives).

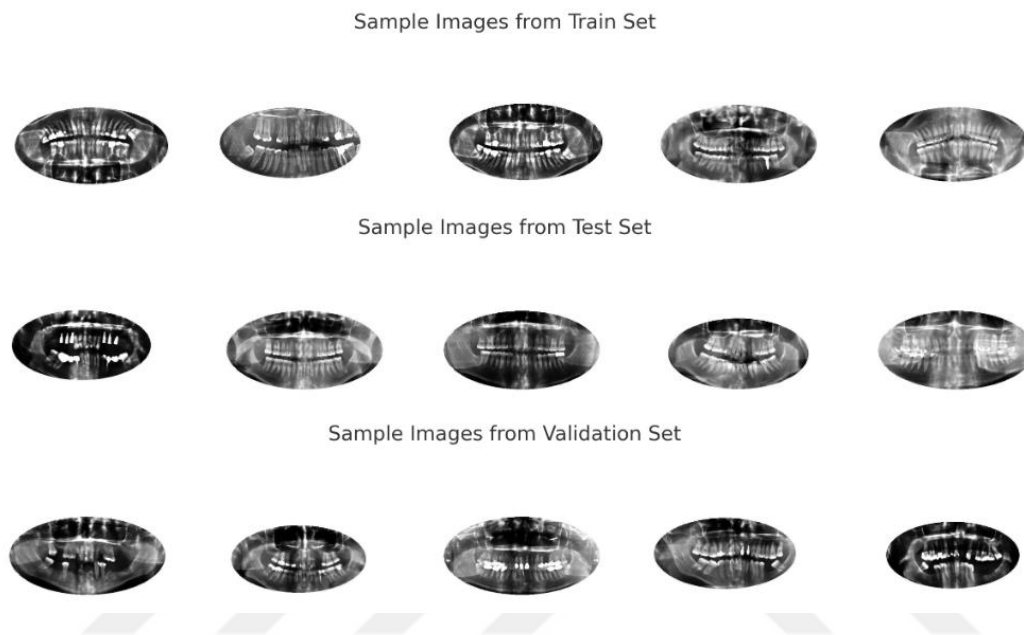
**Recall:** The frequency with which a machine learning model correctly identifies positive examples, or true positives, out of all the real positive samples included in the dataset is quantified by the recall parameter. By dividing the total number of positive events by the true positive rate, recall may be computed. This category includes both false negative findings (missed cases) and true positives (successfully detected instances).

$$\text{Accuracy} = \frac{TP+TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

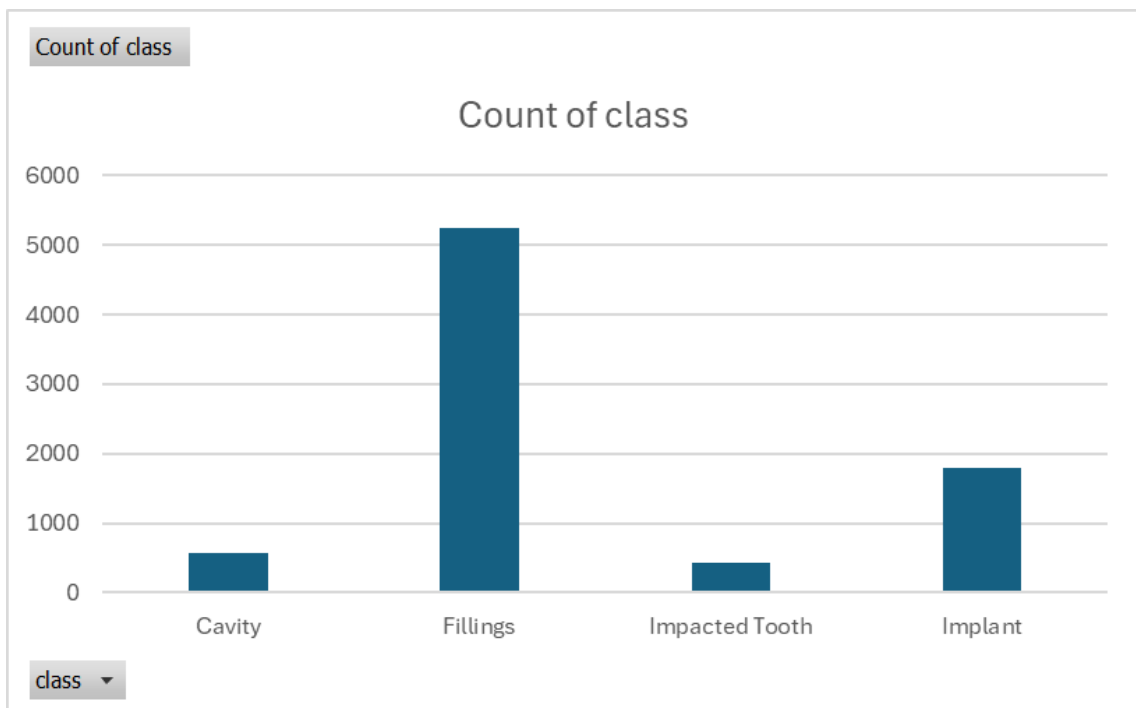
$$\text{Recall} = \frac{TP}{(TP + FN)}$$

Testing Plan: In order to keep model accuracy at maximum, the Train, Test and Valid sets were kept as high as possible. Train sets will enable the model to learn. Valid Set was prepared to evaluate the performance of the model during training and was also used to adjust the hyperparameters of the model. The Test Set is prepared to be used to evaluate the overall performance of the model on independent and never seen data. The image in **Figure 3.1** contains various examples for each dataset.



**Figure 3.1:** Examples of train, test and validation Sets

### 3.1.1. Train dataset



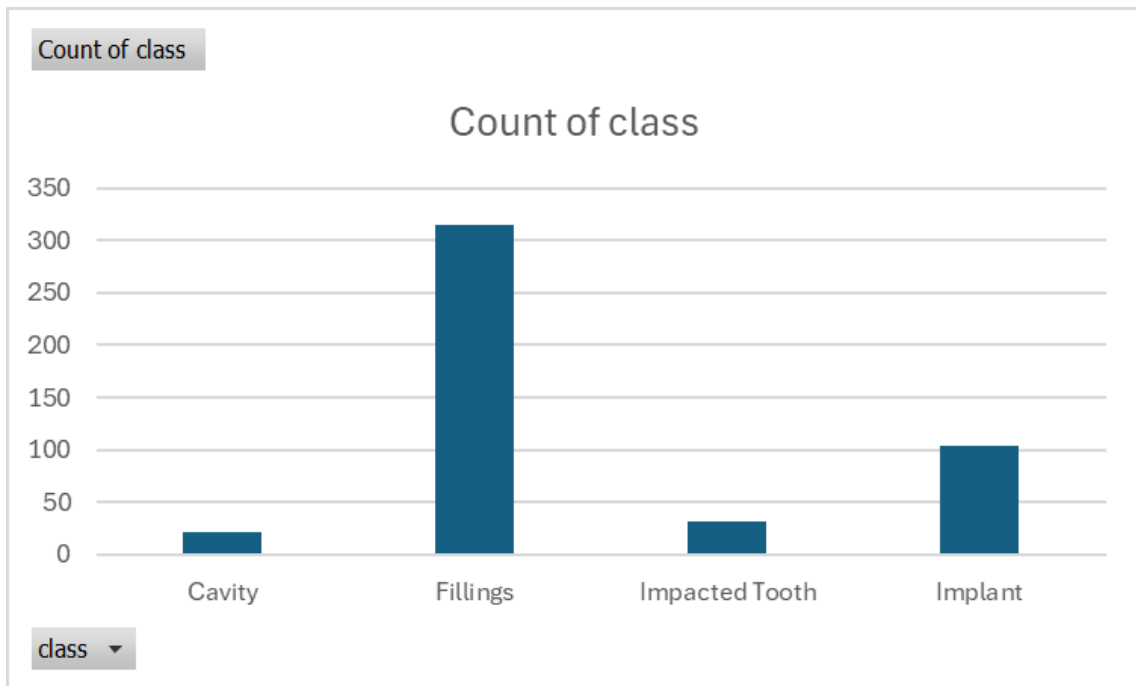
**Figure 3.2:** Class distinctions of the trained data

**Table 1:** Class distinctions of the trained data

Class	Count of class
Cavity	576
Fillings	5242
Impacted Tooth	428
Implant	1784

Training of the model is done with Train sets. In this project, as wide a range of train data as possible was collected and a total of 8030 data were trained. As seen in **Figure 3.2** and Table 1, the model was trained with four different classes: Cavity, Fillings, Impacted Tooth and Implant. First, 576 data were trained from the Cavity class, then 5242 data were trained from the Fillings class, 428 data were trained from the Impacted Tooth class, and finally 1784 data were trained from the Implant class. The more data from the Train data set, the better the model is trained and the error rate decreases, thus the accuracy rate increases. As seen in the result section of this project, we get the highest accuracy rate in the Fillings class because this class model was trained with more data than the others.

### 3.1.2. Test dataset



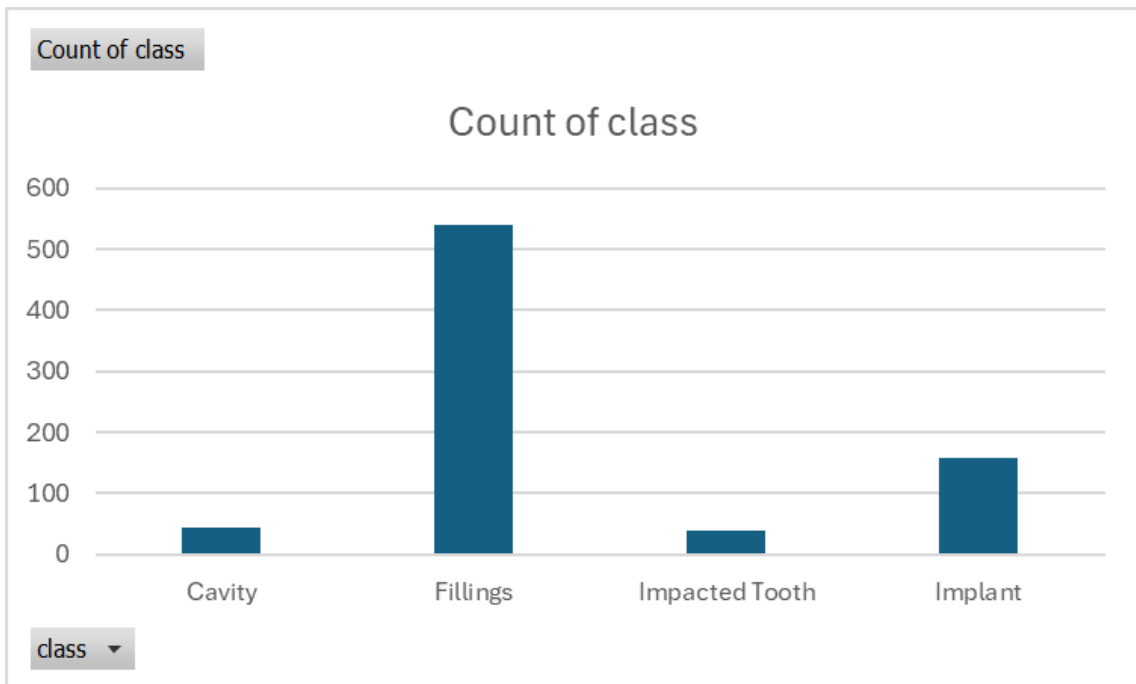
**Figure 3.3:** Class distinctions of the test dataset

**Table 2:** Class distinctions of the test dataset

Class	Count of class
Cavity	22
Fillings	315
Impacted Tooth	32
Implant	104

A test data set was prepared to evaluate the overall performance of the model on independent and never seen data. This phase, which is necessary to understand how the model will perform on real-world data, was never used during training and validation. In the dataset where the model was applied, 22 tests from the Cavity class, 315 tests from the Filling class, 32 tests from the Impacted tooth class, and 104 tests from the Implant class were performed.

### 3.1.3. Valid dataset



**Figure 3.4:** Class distinctions of the valid dataset

**Table 3:** Class distinctions of the valid dataset

<b>Class</b>	<b>Count of class</b>
Cavity	43
Fillings	540
Impacted Tooth	38
Implant	159

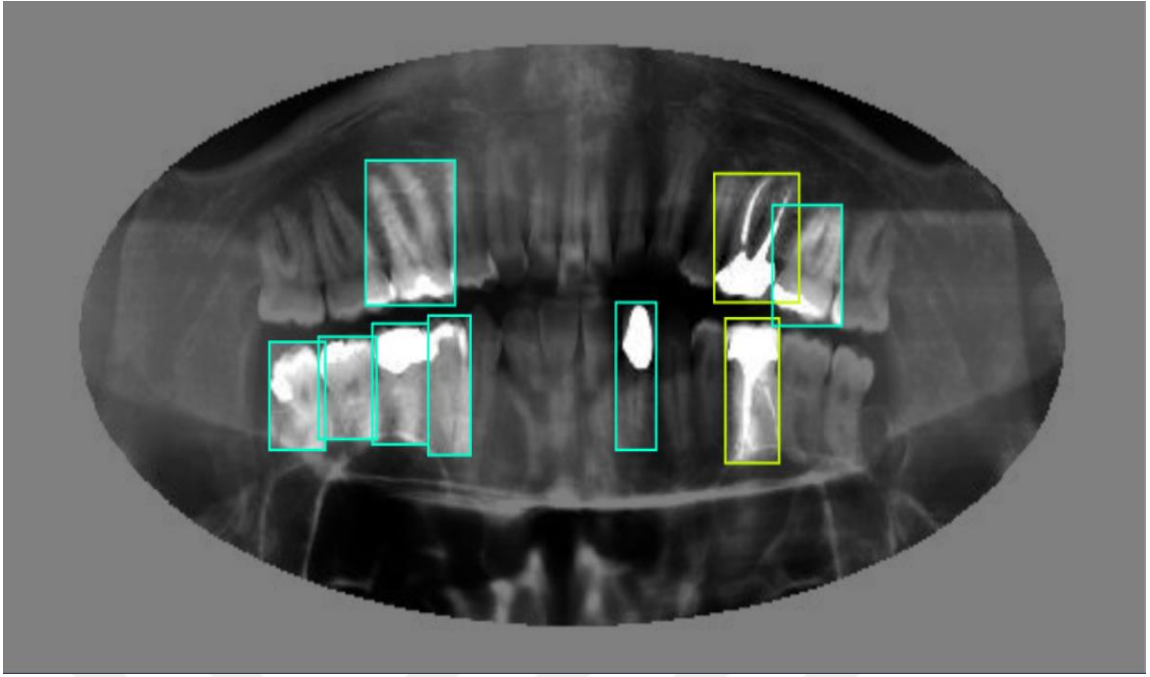
A valid data set was created to evaluate the performance of the model during training and to adjust its hyperparameters. This dataset, which helps prevent overfitting and underfitting, was created from samples from four different categories. In this dataset, 43 data from the Cavity category, 540 from the Filling category, 38 from the Impacted Tooth category, and 159 from the Implant category were used.

## CHAPTER 4

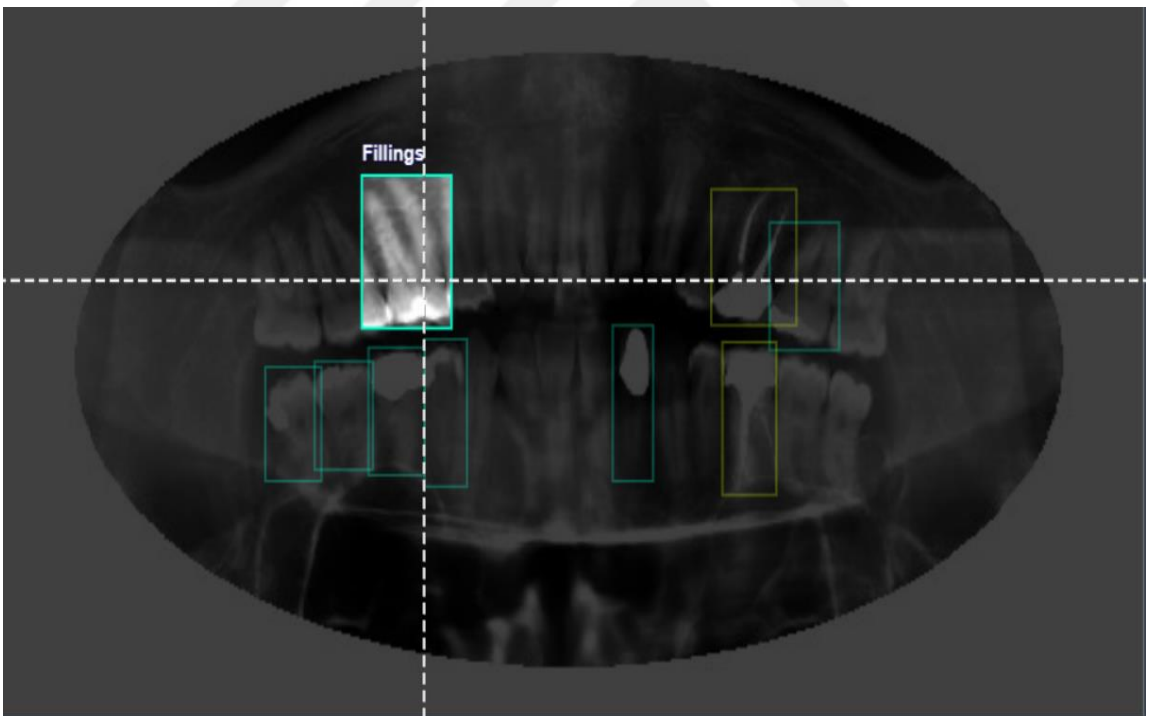
### 4. RESULTS AND DISCUSSION

#### 4.1. Model Results

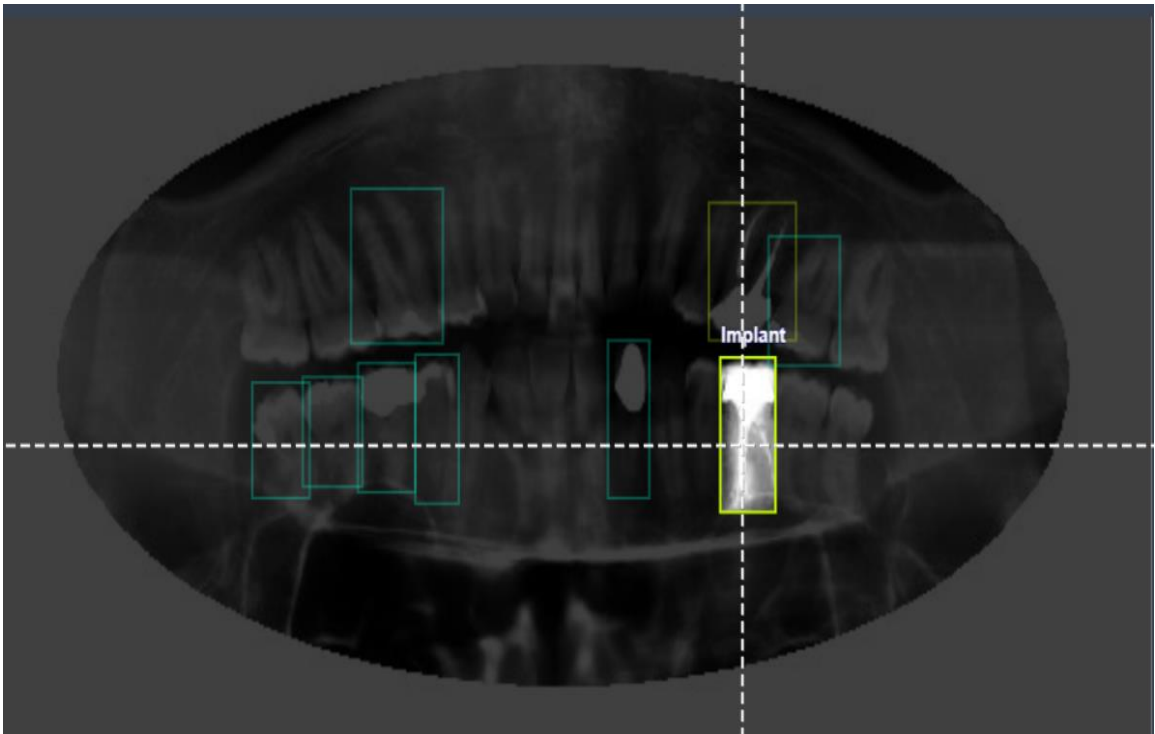
In the project where we aimed to optimize dental examinations and minimize the margin of error in diagnosis, we did first collect data from important public sources such as Kaggle. And then we performed object detection and segmentation using PyTorch and Segmentation Models PyTorch (SMP) libraries. Seeding was done for randomness control and data labels were loaded from the created annotation file. After the image transformations were defined, the Faster R-CNN model was created and the training function was defined. The model was trained for a certain number of epochs and the loss value was recorded after each epoch. After training, the model was saved and loaded again, and then the performance of the model was evaluated using the confusion matrix. **Figure 4.4** shows the results of the complexity matrix. Finally, using the model, inference was made on new images and the predicted classes and bounding box coordinates were printed. This process comprehensively addresses object detection and segmentation using deep learning models. **Figure 4.1** shows object detection and segmentation results.



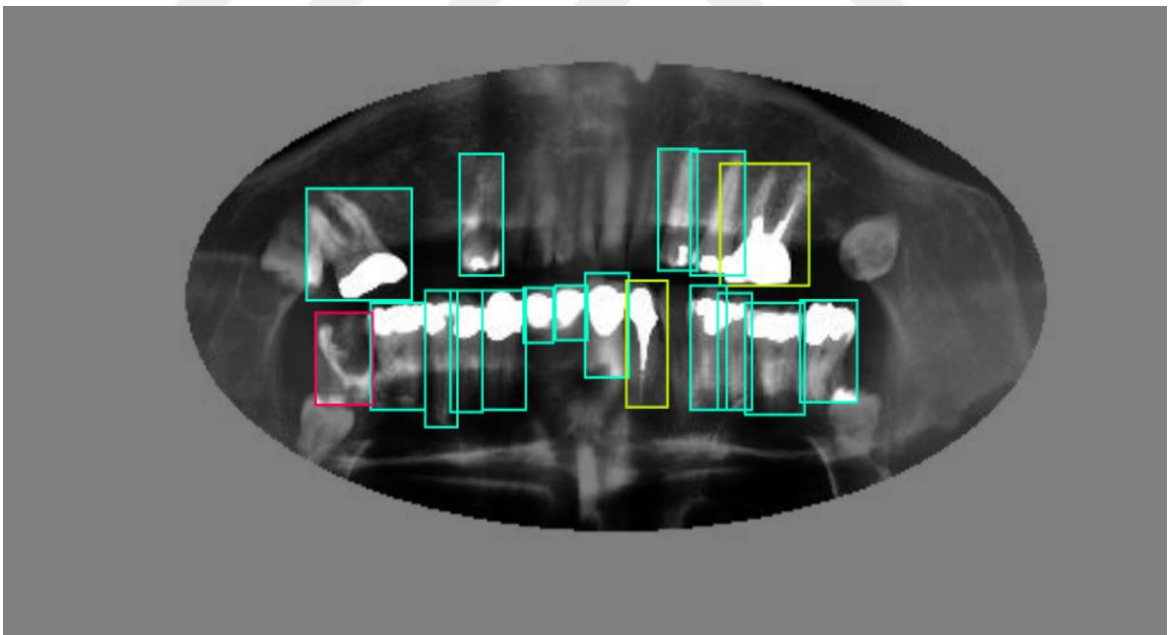
**Figure 4.1:** Object detection result



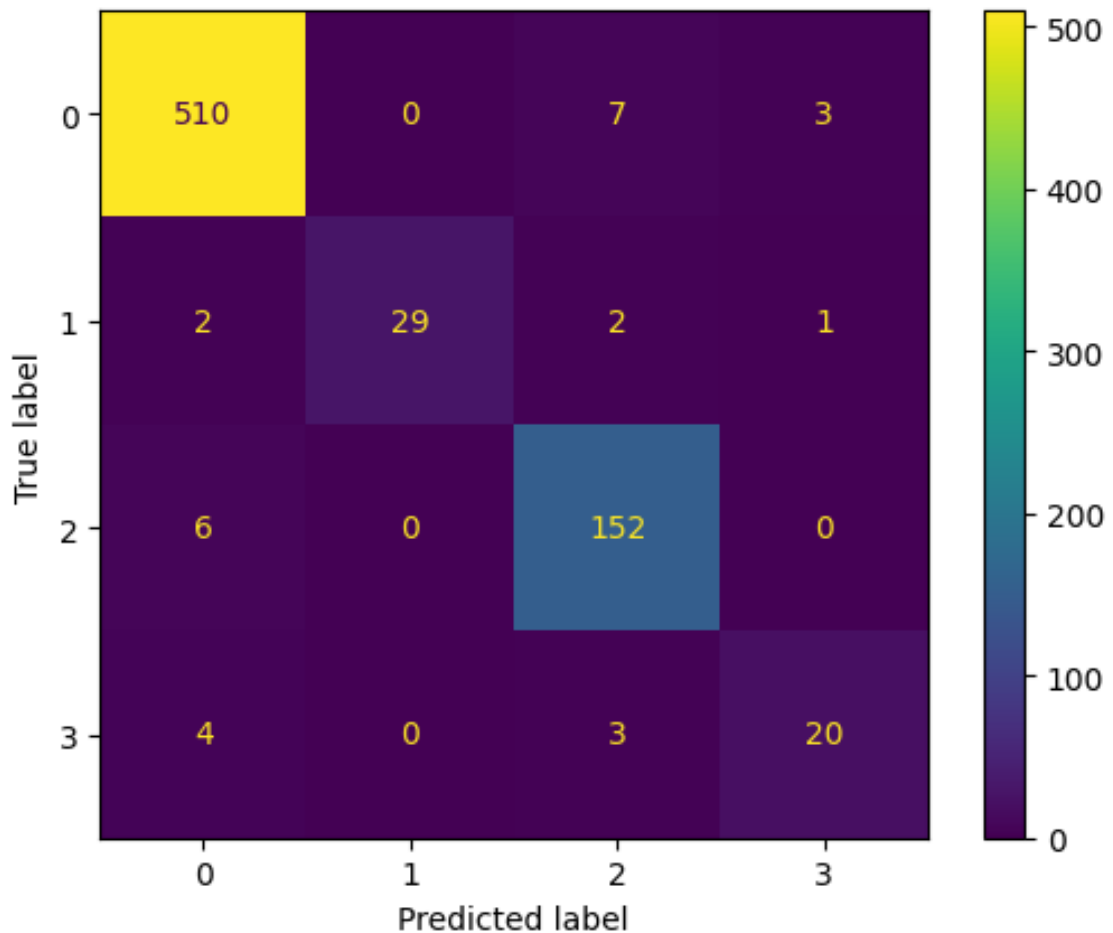
**Figure 4.2:** An example for fillings classification result



**Figure 4.3:** An example for Implant classification result



**Figure 4.4:** Another result example for object detection and segmentation



**Figure 4.5:** Confusion matrix result

As seen in the **Figure 4.5** general Observations;

Class Fillings (Row 0 and Column 0):

Correct predictions: 510

Incorrect predictions: 7 (predicted as Class 2) + 3 (predicted as Class 3)

The model is quite successful in this class because there are only 10 incorrect predictions against 510 correct ones.

Class Cavity (Row 1 and Column 1):

Correct predictions: 29

Incorrect predictions: 2 (predicted as Class 0) + 2 (predicted as Class 2) + 1 (predicted as Class 3)

The model's performance is lower in this class, with correct predictions being almost equal to the misclassifications.

Class Implant (Row 2 and Column 2):

Correct predictions: 152

Incorrect predictions: 6 (predicted as Class 0)

This class is also predicted quite well. The number of incorrect predictions is quite low compared to correct ones.

Class Impacted Tooth (Row 3 and Column 3):

Correct predictions: 20

Incorrect predictions: 4 (predicted as Class 0) + 3 (predicted as Class 2)

The model's performance in this class is relatively low. The correct predictions are few, and the misclassifications are relatively high.

Detailed Analysis:

Class Fillings: The model is very good at recognizing this class. The correct prediction rate is very high. The features of this class might be quite distinctive for the model.

Class Cavity: The model struggles with this class. The correct prediction rate is low, and there is significant confusion with other classes. This suggests that the features of Class 1 may overlap with those of other classes, or the model is insufficient in recognizing this class.

Class Implant: The model performs well in this class too. The incorrect predictions are low, and the correct predictions are quite high.

Class Impacted Tooth: The model's performance is the lowest in this class. The number of correct predictions is low, and there is confusion particularly with Classes 0 and 2. The features of this class may resemble those of other classes.

	precision	recall	f1-score	support
Background	0.00	0.00	0.00	0
Fillings	0.98	0.94	0.96	540
Impacted Tooth	1.00	0.76	0.87	38
Implant	0.93	0.96	0.94	159
Cavity	0.83	0.47	0.60	43
accuracy			0.91	780
macro avg	0.75	0.63	0.67	780
weighted avg	0.96	0.91	0.93	780

**Figure 4.6:** Results of precision, recall, f1 score and support

```

# Assuming y_true are your true labels and y_pred are your predicted labels
accuracy = accuracy_score(y_true, y_pred)
from sklearn.metrics import f1_score
print(accuracy)

# Assuming y_true are your true labels and y_pred are your predicted labels
# Example with 'macro' average
f1_macro = f1_score(y_true, y_pred, average='macro')
print(f1_macro)

# Example with 'micro' average
f1_micro = f1_score(y_true, y_pred, average='micro')
print(f1_micro)

# Example with 'weighted' average
f1_weighted = f1_score(y_true, y_pred, average='weighted')
print(f1_weighted)

# Example with no averaging, getting per-class F1 scores
f1_per_class = f1_score(y_true, y_pred, average=None)
print(f1_per_class)

```

```

0.9115384615384615
0.6728630030307089
0.9115384615384615
0.9318696035887745
[0.          0.96045198 0.86567164 0.94117647 0.59701493]

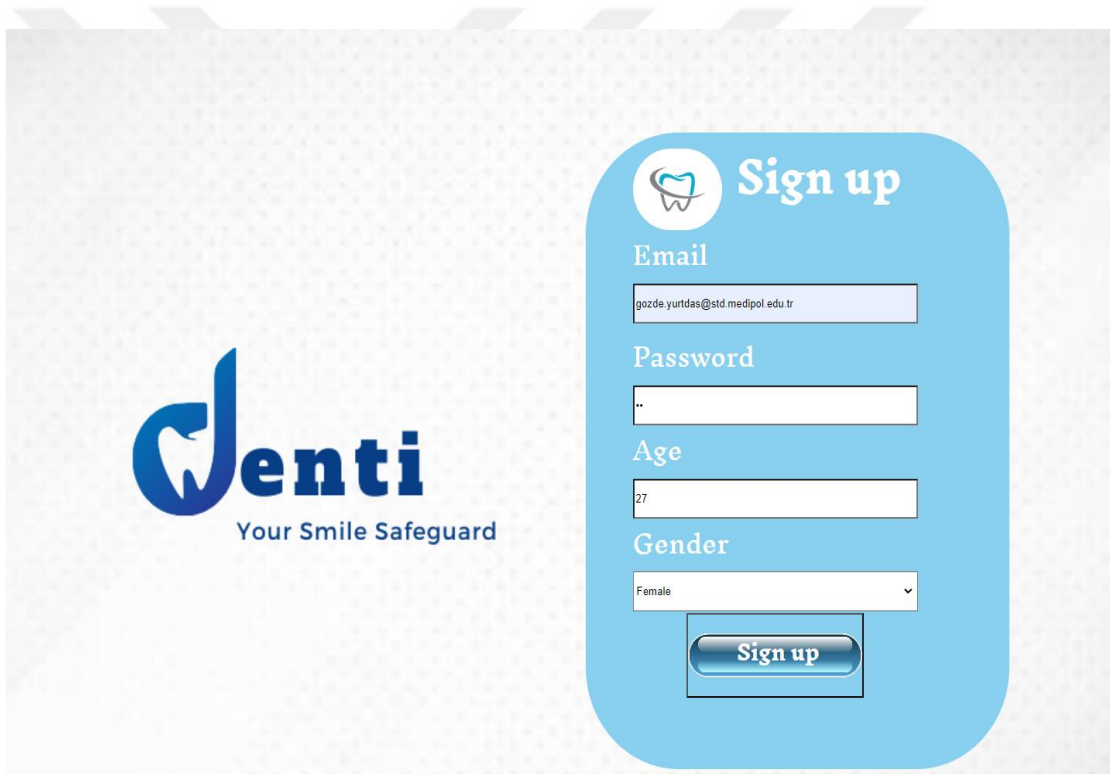
```

**Figure 4.7:** Results of F1 score

When we look at the results in **Figure 4.6** and **Figure 4.7**, we see that the classification model has a very successful performance in detecting various conditions related to dental

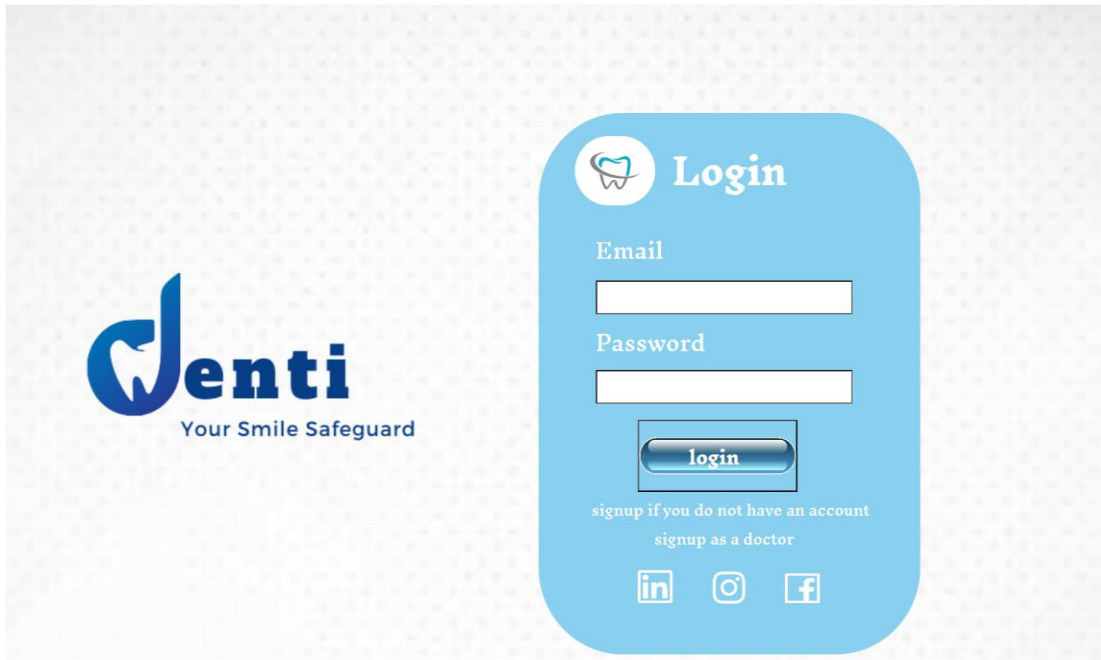
health. Superior results were obtained especially in the fillings (precision: 0.98, sensitivity: 0.94, F1: 0.96) and implants (precision: 0.93, sensitivity: 0.96, F1: 0.94) classes. The overall accuracy of the model is at a high level of 91%, and the weighted F1 score of 0.93 shows how strong the overall performance is. Although the macro average F1 score is 0.67, it is noteworthy that the model shows high performance, especially in classes with more samples (fillings and implants). Although some improvements are needed due to lack of data in the caries class (precision: 0.83, sensitivity: 0.47, F1: 0.60), it is generally possible to say that the model is an effective and reliable tool for dental health diagnostic systems.

## 4.2. Interface



**Figure 4.8:** Sign up page

On the sign up page, users can register as a patient or doctor. If the user wants to register as a patient, he/she fills out the relevant form; If he wants to register as a doctor, he fills out a special registration form for doctors. In this way, appropriate accounts are created according to the users' roles.



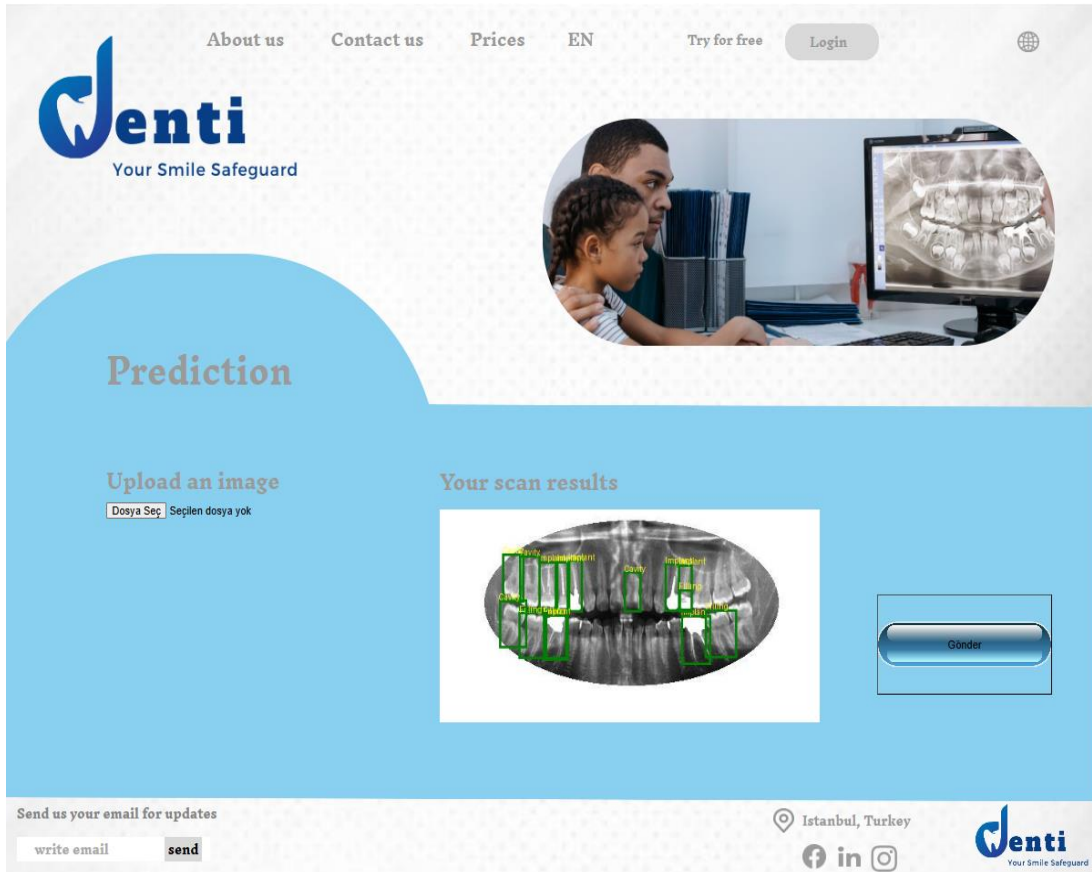
**Figure 4.9:** Login page

There are two separate logins for doctors and patients on the login page. Patients can log in to their accounts from the patient login, while doctors can log in to their accounts from the doctors login screen.



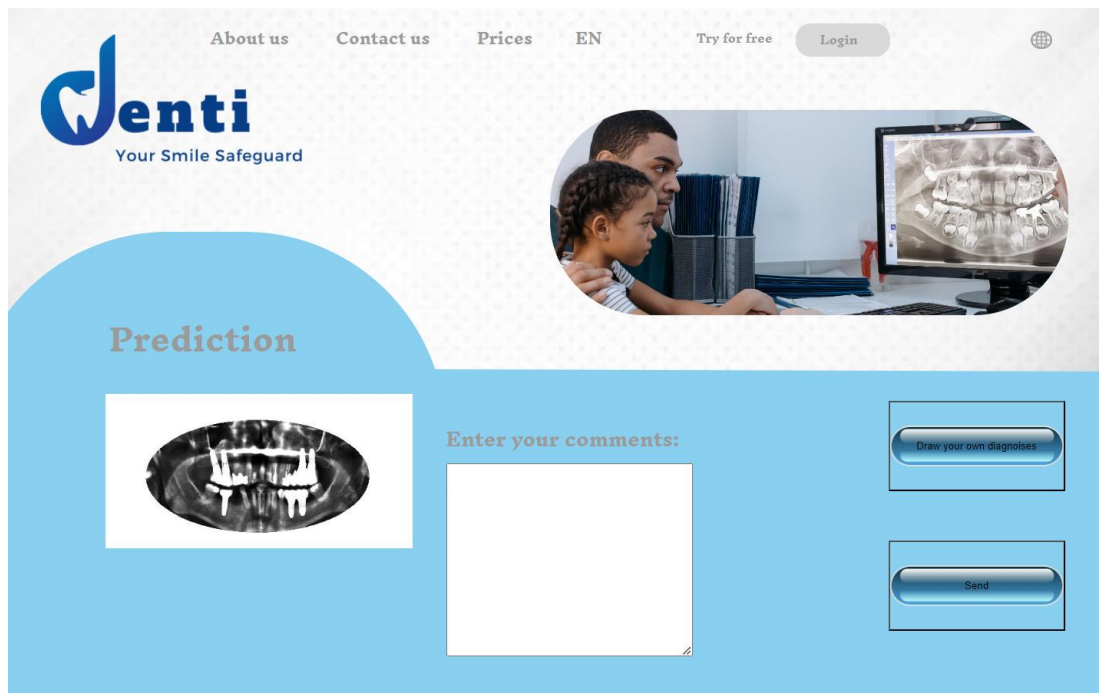
**Figure 4.10:** Home page

On the homepage, there are pages such as features, details, price, contact us, login and about us.



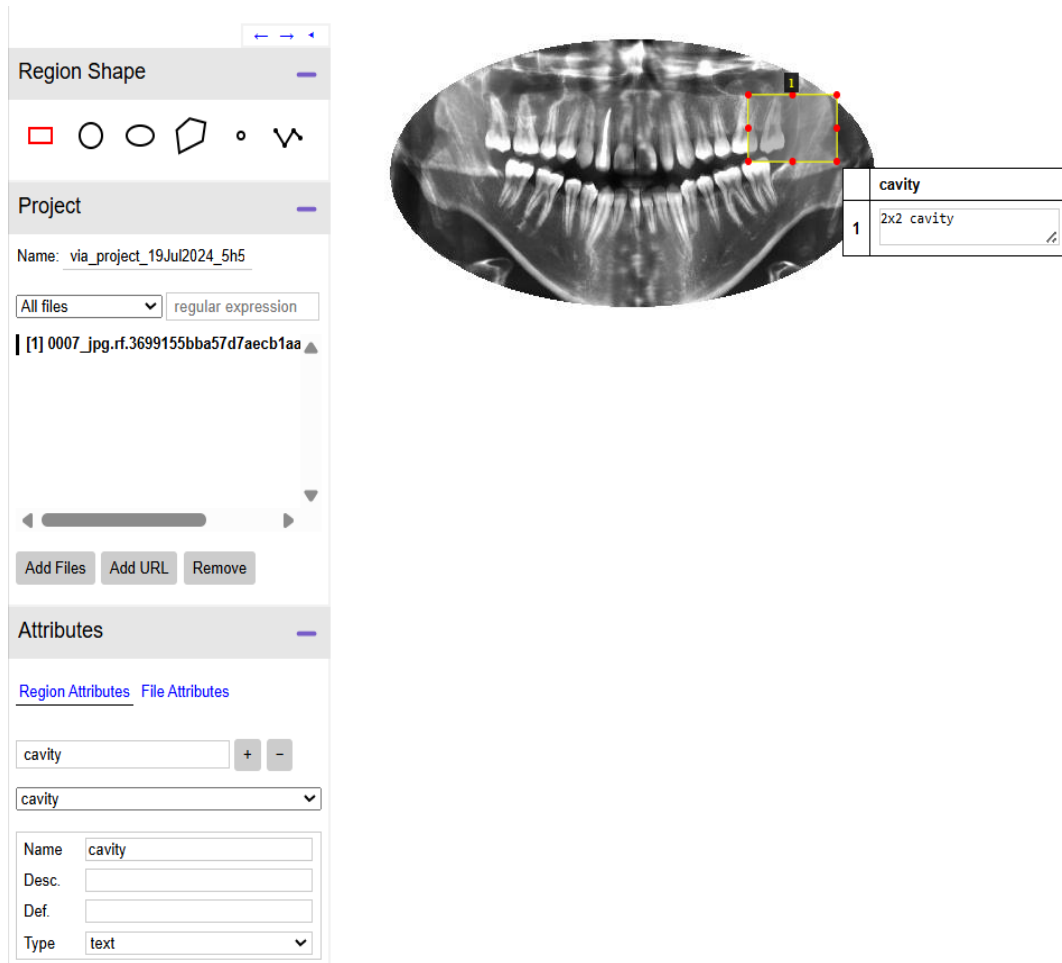
**Figure 4.11:** Patient instants diagnose page

This is the page where patients can directly upload their own x-ray results from the Instant Diagnose section. When patients upload their x-ray results, they can automatically see their diagnoses visualized.



**Figure 4.12:** Doctors diagnose page

The doctors' diagnosis page is a little different, here doctors can write and send comments on the uploaded results, and they can also direct you there if they want to draw their own diagnoses on the results.



**Figure 4.13:** Page where the doctor can visualize the diagnosis

Doctors can navigate to the tool shown in **Figure 4.13** from the diagnosis page, where they can draw the diagnosis sections themselves, as seen in the picture.

## **CHAPTER 5**

### **5. CONCLUSIONS AND FUTURE WORK**

The aim of this project is to minimize the margin of error in the diagnosis process in X-ray dental x-ray images and to optimize dental systems. As a first step in this direction, we started by creating the most accurate data set for the purpose and model training was carried out using 8031 data. Data was fed regularly to increase the accuracy of the model. Then, segmentation was applied to all of the data to ensure high quality image processing. After the segmentation process, classification was made into four different diagnostic categories. These classification categories are: Cavity, Impacted tooth, Fillings and Implant. As a result of the tests, the reason why the highest accuracy rate is seen in the Fillings category is that there is the most data in this category. Considering the overall accuracy rate, an accuracy rate of 91% was obtained as a result of the F1 score tests.

Afterwards, an API was created and an interface was developed using FastAPI with these models. This interface has two different login tabs: Patient login and doctor login. With patient login, patients register with their own information and create an account, and then they can enter their x-ray results on this page and get their diagnosis. Doctor login allows doctors to register, select patients' x-ray results and write diagnostic comments about the results. Additionally, doctors can visualize these diagnoses with a drawing tool. A more detailed analysis is planned as a future work. For example, bacterial density in caries can be studied, a more optimized system can be established, for example, there may be sections where other doctors can comment and comparisons can be made. As another future study, diagnostic categories may be increased.

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## **PUBLICATIONS, PRESENTATIONS, AND PATENTS ON THE THESIS:**

- G. Yurtdas, K. Aslan, S. T. Özyer, T. Özyer, M. Kaya and R. Alhadj, "A Prediction Approach for the Functional Effects of Non-Coding Gene Variants," 2022 International Arab Conference on Information Technology (ACIT), Abu Dhabi, United Arab Emirates, 2022, pp. 1-6, doi: 10.1109/ACIT57182.2022.9994094.
- G. Yurtdas, K. Aslan, S. T. Özyer, T. Özyer, M. Kaya and R. Alhadj, "A Prediction Approach for the Functional Effects of Non-Coding Gene Variants," 2022 International Arab Conference on Information Technology (ACIT), Abu Dhabi, United Arab Emirates, 2022, pp. 1-6, doi: 10.1109/ACIT57182.2022.9994094.

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Konu : Etik Kurulu Kararı

28/05/2024

**Sayın Gözde Yurtdaş**

Üniversitemiz Girişimsel Olmayan Klinik Araştırmalar Etik Kuruluna yapmış olduğunuz 'X-Ray Dental Verilerinde Otomasyonlu Tanı: Segmentasyon ve Sınıflandırma Yöntemleri ile Geliştirilen Yenilikçi Sistem' isimli başvurunuz Etik Kurulumuzca değerlendirilerek uygun görülmüş olup Etik Kurulu kararı ekte sunulmuştur.

Bilgilerinize rica ederim.

**Dr. Öğr. Üyesi Mahmut TOKAÇ**  
Girişimsel Olmayan Klinik Araştırmalar  
Etik Kurulu Başkanı

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ETİK KURULU KARAR FORMU

<b>BAŞVURU BİLGİLERİ</b>	<b>ARAŞTIRMANIN AÇIK ADI</b>	X-Ray Dental Verilerinde Otomasyonlu Tanı: Segmentasyon ve Sınıflandırma Yöntemleri ile Geliştirilen Yenilikçi Sistem			
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<b>Karar Bilgileri</b>	<b>Karar No: 520</b>	<b>Tarih: 22.05.2024</b>				
	Yukarıda bilgileri verilen Girişimsel Olmayan Klinik Araştırmalar Etik Kurulu başvuru dosyası ile ilgili belgeler araştırmanın gerekçe, amaç, yaklaşım ve yöntemleri dikkate alınarak incelenmiş ve araştırmanın etik ve bilimsel yönden uygun olduğuna <b>"oybirliği"</b> ile karar verilmiştir.					

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Unvanı/Adı/Soyadı	Uzmanlık Alanı	Kurumu	Cinsiyet		Araştırma ile İlişki		Katılım *		İmza
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# AUTOMATED DIAGNOSIS IN X-RAY DENTAL DATA: INNOVATIVE SYSTEM DEVELOPED WITH SEGMENTATION AND CLASSIFICATION METHODS

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