Teeth Problem Detection Using Deep Learning and Image Processing Technology

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***Abstract*—Dentists often rely on dental X-rays to spot cavities, bone loss, and hidden dental issues not visible to the naked eye. These X-rays help catch problems early and create effective treatment plans. We look at three types of X-rays: bitewing, periapical, and panoramic. Bitewing X-rays show part of the upper and lower teeth and help find bone density changes due to gum disease. Periapical X-rays show all teeth and help check the bone and roots in the upper and lower jaw. We also use technology to determine a patient's age and detect early signs of oral cancer from these X-rays. This survey summarizes how technology improves dental care byhelping dentists diagnose and treat oral health problems effectively. It's a win-win for both dentists and patients.**

Keywords: Deep Learning, Image Processing, X-rays, Dentists,Cavities, Age Detection, Oral Cancer, disease, CNN

I. INTRODUCTION

Oral health is an integral component of overall well-being, and early detection of dental issues is essential for effective treatment and patient care. Dentists have long relied on dental radiographs to uncover problems such as cavities, bone loss, and hidden dental issues that remain concealed to the naked eye. These radiographs, also known as dental X-rays, serve as invaluable tools for dental practitioners, enabling them to identify, diagnose, and treat dental conditions in a timely and precise manner.

In recent years, the integration of deep learning and image processing techniques has brought about a transformation in the way we approach dental diagnostics. This paper focuses on the amalgamation of advanced technology with dentistry to create a powerful synergy for the detection of dental issues. Beyond conventional dental radiographs, this research delves into the incorporation of deep learning and image processing techniques for oral cancer detection and age determination. This multifaceted approach not only enhances the diagnostic capabilities of dentists but also opens new avenues for preventive care and early intervention.

The overarching objective of this research paper is to provide a comprehensive overview of the groundbreaking advances in the field of dental diagnostics. We explore how deep learning, a subset of artificial intelligence, and image processing, a method of enhancing and analyzing images, are leveraged to elevate dental care to new heights. By harnessing the power of technology, we aim to improve the precision and speed of diagnosis, ultimately leading to better patient outcomes.

The following sections of this paper will delve into the specific applications of deep learning and image processing in dental diagnostics, including the analysis of dental radiographsand their role in detecting cavities, bone loss, and hidden dentalissues. We will also delve into the innovative utilization of these technologies for age detection from dental X-rays and the early identification of oral cancer. As we embark on this journey through the convergence of dentistry and cutting-edgetechnology, it is evident that these advancements are poised to revolutionize the field, providing a win-win scenario for both dental professionals and patients. With the potential to detect and treat dental problems more efficiently and effectively, this research contributes to the ever-advancing landscape of healthcare, emphasizing the importance of early diagnosis and personalized care in the realm of oral health.

II. RELETED WORK

In the field of dental informatics there are many approaches developed for teeth problem detection using different types of radiographic images such as bitewing, periapical and panoramic images. In [18] R. Dharani and S. Revathy address the significant issue of oral cancer, which ranks as the eighth most common global cancer, causing 130,000 annual deaths in India. Traditional diagnostic methods often struggle to precisely identify and quantify cancer cells. To tackle this, the study utilizes digital processing technology and advanced learning algorithms to detect and classify cancer- affected cells in the oral region. In [19] Lavanya L1 and Dr. Chandra J. address the crucial task of oral cancer staging, vital for tailoring treatment. They explore both clinical (TNM system) and pathological (histology, p63, podoplanin) staging methods and leverage machine learning techniques to classify different oral cancer stages. Their research, centered on Oral Leukoplakia data, involves data standardization and feature extraction via correlation coefficients. Results reveal that

Random Forest and Decision Trees efficiently classify various oral cancer stages, offering promising classification solutions. In [21] Isa Ataş, Cüneyt Ozdemir, Musa Ataş, and Yahya Doğan present a study emphasizing the significance of dental age estimation for determining an individual's age, especially in forensic sciences where records are lacking. They tackle thelabor-intensive and time-consuming nature of current methods with deep learning algorithms in medical image processing, aiming to enhance accuracy and speed. In [22] Noor Mualla, Essam Houssein, and M. R. Hassan, the focus lies on the crucial task of chronological age estimation using panoramic dental X- ray images within the field of forensic sciences. While various statistical methods have been considered, there is a growing need for automated dental age estimation through machine learning techniques. The research introduces an automated approach employing transfer learning, with feature extraction utilizing deep neural networks like AlexNet and ResNet.

In "Tooth Detection and Segmentation with Mask R-CNN" this paper, we expound the application of Mask RCNNon au- tomatic tooth detection and segmentation. Mask RCNN is a recently proposed sur- prising algorithm for objectdetection and semantic segmentation. This paper aims at detecting and segmenting tooth only. We show that Mask RCNN also has a good segmentation effect in complex and crowded teeth structures. We use the pixel accuracy (PA) to evaluate the results. In "Bucket Teeth Detection Based on Faster Region Convolutional Neu- ral Network" this paper addresses electric shovel is a bucket-equipped mining excavator widely used in open-pit mining today. The prolonged direct impact of the bucket teeth with hard and abrasive materials such as ore during the process of the mining excavation can cause the bucket teeth to break and fall off prematurely, resulting in unplanned downtime and productivity losses. In response to this problem, we have developed a vision-based bucket teeth fault detection algorithm with deep learning. Using a dataset based on the images of both real shovel teeth and 3D-printed models, we trained a Faster Region Convolutional Neural Network (Faster R-CNN) to obtain the number of normal bucket teeth and the positions of the bucket teeth from the images, using the additional bucket dataset from 3D-printed models to pre- train the network for improving its detection accuracy on the real bucket data. We compared the re- sulting Faster R-CNN model with the ZFNet, the ResNet-50, and the VGG16 and found our Faster R-CNN model to perform best in terms of accuracy and speed. In "A Vision System for Detecting Missing Tooth in Rope Mine Shovel" this Rope shovels are widely used in the mining industry to dig ore. During operation, one or more teeth in the bucket can be lost as a result of the force that impacts the teeth, which causes a serious problem when the broken teeth gets picked up by the haul truck and eventually ended up in the crusher and jamming it.

In this paper, we present a vision system for monitoring tooth condition and detecting missing tooth for a mining shovel. Our system leverages the predictable range of motion that the bucket of a rope shovel goes through during operation due to the camera mounting. For this reason, our strategy is to use exemplar based image retrieval and a sliding window procedure to first locate a pre-defined static region ofthe bucket in a live frame, followed by detecting the tooth line region based on its relative position to the selected exemplar. Once the tooth line region is detected, we proceed by determining its transformation from a recently detected tooth line region, and rectify the tooth line region before conducting image differencing. Se-Ryong Kang, Jun-Min Kim, Sul-Hee Kim, Hee-Jung Park, Tae-Il Kim, and Won-Jin Yi presents work on Tooth cracks detection and gingival sulcus depth measurement using optical coherence tomography. The aims of this study were to develop an automatic detection technique for tooth cracks and to suggest quantitative methods for measuring gingival sulcus depth using swept-source optical coherence tomography. Guohua Zhu, Zewen Piao, Suk ChanKim presents a work that perform Detection and Segmentation with Mask R-CNN. In this paper, we expound the application of Mask RCNN on automatic tooth detection and segmentation. Mask RCNN is a recently proposed surprising algorithm for object detection and semantic segmentation .

Our paper builds upon the state of the art by proposing a novel segmentation and classification method using a semantic segmentation CNN and multiple image processing techniques, which are applied on panoramic X-Ray images. Each tooth is labeled and segmented and the main problem that is affecting it is determined. In our paper we had implemented age detection of patient's and according to age treatment is given to patient. We also implement oral cancer detection module.

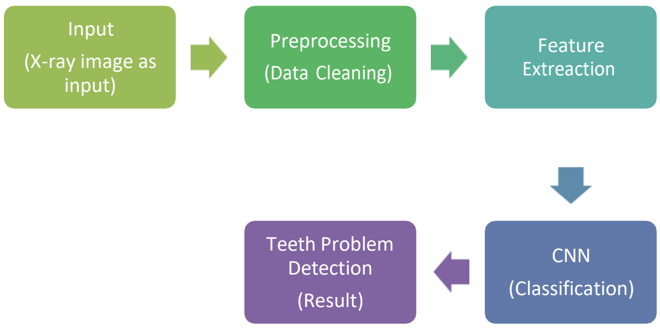

Fig.1 Main components of processing pipeline.

III. PROPOSED SOLUTIONS

A. *Image Preparation*

In this section the main contributions of this paper will be explained in more detail. The panoramic X-ray radiographies, used in this study, were obtained from three different dental clinics. The images contained various tooth problems such as restorations, dental implants, dentures and others. The main modules of the processing pipeline are presented in Figure 1.

Image preparation is a crucial step in any image processingand deep learning research, particularly when working with medical or dental images. Properly prepared images lead to more accurate results and smoother model training. In this stage all of the images were cropped in order to remove any name that was present on the radiography and then they were renamed thus anonymizing the identity of the people.

Afterwards, the images were resized to the dimensions of 2048x1024 pixels. The next step was annotating at pixel levelall these images with 14 different classes each class corresponding to a specific tooth problem and another one for background, summing 15 classes in total. From the original dataset that contains approximatively 2000 images, 1000 images were selected and annotated for semantic segmentation. The selected semantic classes are: healthy tooth, missing tooth, dental restoration, implant, fixed prosthetics work, mobile prosthetics work (dentures), root canal device, fixed prosthetic work and root canal device, fixed prosthetic work and implant, fixed prosthetic work and devitalized tooth, devitalized tooth and restoration, dental inclusion, polished tooth, another problem and background. The last step in this stage was generating the corresponding labels for these classes.

B. Feature Extraction Techniques

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data. Use traditional image processing techniques to extract relevant features from the ROIs. These techniques may include edge detection, texture analysis, and color analysis. For example, we have use methods like Canny edge detection, Gabor filters, or histograms. For extracting deep Learning-Based Features weutilize pre-trained deep learning models like convolutional neural networks or CNNs to extract features from dental images. Transfer learning can be beneficial, as it allows we touse models pre-trained on large datasets (e.g., ImageNet) to extract relevant features. The output of intermediate layers in a CNN can also be used as features. For shape Analysis tasks like tooth alignment or identifying specific structural issues, we want to extract shape-based features. Tools like contour detection and shape descriptors can be helpful.

C. CNN Algorithm

A convolutional neural network (CNN) is a subset of machine learning. It is one of the various types of artificial neural network which are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. Convolutional Neural Networks (CNNs) are a class of deep neural networks primarily designed for tasks that involve visual data, such as image andvideo recognition, object detection, and image classification. CNNs are characterized by their ability to automatically learn and extract hierarchical features from images, making them well-suited for computer vision tasks. CNNs have had a profound impact on the field of computer vision and have been integral in achieving state-of-the-art results in various image-related tasks. They continue to be a fundamental technology in deep learning and artificial intelligence. Here's how CNNs work in the context of teeth problem detection using deep learning and image processing techniques:

Convolution Operation: CNNs use a set of learnable filters or kernels. These filters are small, square-shaped matrices (typically 3x3 or 5x5) that slide over the input image. At each position, the filter computes the dot product between its weights and a small region of the input image, known as the receptive field.This operation captures local patterns, edges, and features within the image. Feature Maps : The result of the convolution operation is a feature map, which highlights specific features or patterns in the image. CNNs typically use multiple filters to generate multiple feature maps, each capturing different aspects of the input. Activation Function

: After convolution, an activation function (commonly ReLU - Rectified Linear Unit) is applied element-wise to the feature maps. The activation function introduces non-linearity, allowing the network to learn complex patterns and relationships. Pooling (Subsampling) Layer : Pooling layers, often MaxPooling or AveragePooling, down-sample the feature maps. Pooling reduces the spatial dimensions of thefeature maps, which helps to reduce computation and makes the network more robust to translations and distortions in the input.

Fully Connected (FC) Layers : After several convolution and pooling layers, the network typically ends with one or more fully connected layers. These layers perform classification tasks by learning to combine the features from the previous layers. For teeth problem detection, the output of the fully connected layer(s) can represent the probability of different dental problems, with each neuron corresponding to a specific class. Softmax Activation : The final layer often uses the softmax activation function to convert the network's raw output into probability scores. The class with the highest probability is considered the predicted class, indicating the presence or absence of a specific dental problem. Training : CNNs are trained using a labeled dataset of dental images. The network learns to adjust its parameters (filter weights) during training to minimize the difference between its predictions and the actual labels. Backpropagation and optimization techniques like Stochastic Gradient Descent (SGD) are used to update the filter weights. Loss Function: A loss function, such as cross-entropy, measures the dissimilarity between the predicted probabilities and the true labels. The goal during training is to minimize this loss function. Evaluation:After training, the CNN is evaluated on a separate testing dataset to assess its accuracy, sensitivity, specificity, and other relevant performance metrics. Post-Processing: Depending on the specific dental problem detection task, post-processing techniques may be applied. For example, if the task involves identifying the location of a cavity, additional processing maybe needed to localize the problem area within the image. In the context of dental image analysis, CNNs can be customized toidentify a range of dental problems, such as cavities, gingivitis,or tooth abnormalities.

By training on a diverse and well-prepared dataset, CNNs can learn to recognize patterns and features within dental images, making them a powerful tool for automating the detection of dental problems. By using these robust mechanism age of patient can be determined ,which is helpful to give treatment to patient.

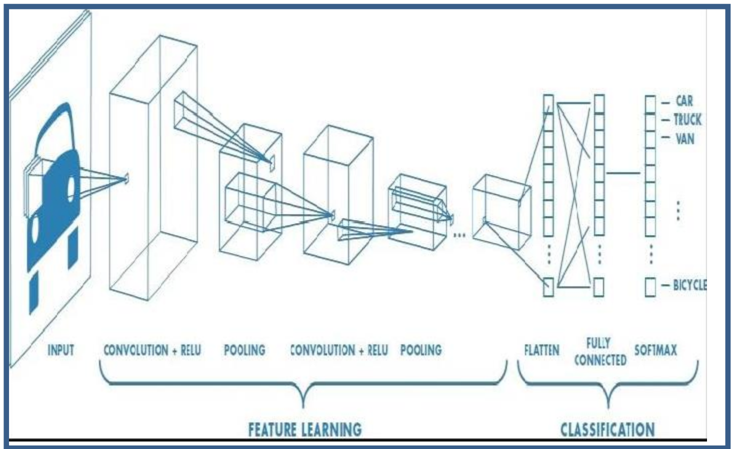

Fig.2 Neural network with many convolutional layers

IV. CONCLUSION AND FUTURE WORK

In this project, we have presented a comprehensive exploration of dental problem detection, classification, age determination, and oral cancer detection using advanced deep learning and image processing techniques. Our research has shown that these innovative methods hold great promise in enhancing dental diagnostics and patient care.Through the utilization of panoramic X-ray images, our proposed approach for automatic teeth detection and dental problem classification provides an efficient and reliable tool for dental practitioners. The accurate identification of dental issues enables early intervention and treatment planning, ultimately improving patient outcomes and well-being. Additionally, our investigationinto age detection using dental images has the potential to offer a unique biometric identifier for individuals, which may find applications in various healthcare and forensic scenarios. Furthermore, early oral cancer detection using these techniques can significantly increase the chances of successful treatment and, in some cases, save lives .

For future work, we aim to improve the running timeof the proposed solution using hardware acceleration methods. Furthermore, we would like to increase the accuracy of the proposed solution and include more semantic classes.

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