

Using Deep Neural Networks and Image Processing to Identify and Categorize Dental Issues in Panoramic X-Ray Images

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Abstract—In recent years, X-rays and other forms of medical imaging have aided dentists in the diagnosis of a wide range of oral health problems. The buccal cavity and other hard-to-reach locations are two places where dental professionals might benefit from the study of panoramic dental x-rays to spot potential issues. The diagnosis may change, however, because of poor image quality or weariness, which might have an impact on the therapy. To aid dentists in establishing accurate diagnoses, this study introduces a unique approach to automated tooth recognition and dental condition categorization utilizing U-Net Models and real-time panoramic X-Ray pictures. The researchers in this study gathered panoramic radiographs from dental offices and analysed them to identify 20 distinct tooth problems. A convolutional neural network (CNN) was trained to acquire semantic segmentation data using the annotated data. In addition, procedures for the processing of images such as semantic segmentation, picture pre-treatment, and increased bounding boxes matching teeth detections were carried out.

I. INTRODUCTION

Diagnostic imaging techniques like computed tomography (CT) and X-rays have been increasingly used in the area of dentistry to aid in the detection of a wide range of diseases in recent years [1]. High-resolution image sensors and biosensors provide large datasets that can be evaluated by computers to help dentists with their decisions on anything from preventative care to treatment plans. Images may be captured by projective radiography by directing X-rays from an X-ray source into the mouth.[1] Some organs may take up radiation, or the radiation can pass through the body and be picked up by a sensor [1][2]. Produces flat, two-dimensional images of the human body's organs and systems. Dental radiographs may be taken either intraorally, with the film positioned within the buccal cavity, or extraorally, with the patient positioned between the X-ray source and the radiographic film. Intraoral bitewing and periapical X-rays, as well as panoramic X-rays, are the most typical, but extraoral panoramic X-rays are also used. All of the teeth in a patient's mouth may be seen on a panoramic x-ray of their mouth[2]. The dentist may get a good look of the patient's jaws and skull to get a sense of the full scope of their issues. Dentists utilize panoramic dental x-rays to examine the buccal cavity, which is sometimes difficult to see inside[2]. Nevertheless, difficulties in analysis might arise and lead to incorrect interpretation if the X-ray radiography is not clear.

To analyze medical images, Convolutional Neural Networks (CNN) are widely used. Using CNNs has shown effectiveness in a variety of contexts, including as the evaluation of mammography for breast cancer, the detection of skin cancer in clinical skin examinations, and the identification of regions of hepatocellular

carcinoma in ultrasound imaging [4]. One of the primary objectives was to train a semantic segmentation system using manually annotated panoramic x-rays. Semantic CNN segmentation of a panoramic X-ray picture for 20 semantic classes representing common dental issues [3]. The goal is to use a variety of image processing methods to identify each affected tooth or set of teeth, as well as the specific dental issue impacting them. The goal of this technique for refining is to reduce inconsistencies that are not very significant and to evaluate the proposed solution in light of other CNNs that have been produced for the same function with the intention of making it more effective[3].

Experts in the field of dentistry using panoramic radiography often find issues in previously inaccessible places, such as the inside of the buccal cavity or areas with limited sight. The diagnosis may vary, however, due to factors such as low imaging quality or weariness. Thus, the medical team need a technique for teeth recognition and dental issue categorization using panoramic X-Ray pictures to help in the accurate diagnosis.[1][2]

To aid dentists in making an accurate diagnosis utilizing panoramic dental X-ray pictures, we present a deep learning approach in this study. Here are some examples that show the paper's primary contributions:

- huge quantities of data that are capable of being processed by computer algorithms in order to assist dental practitioners in a range of decision-making processes, including prevention, diagnosis, and therapy planning.
- We use a convolutional neural network (CNN) to the panoramic X-ray image to semantically segment it into 15 categories reflecting different dental problems.
- Using a variety of image processing methods, we identify each affected tooth or set of teeth and the dental issue that has caused it.
- We use a process of refining to get rid of the minor discrepancies.
- The suggested solution is analysed and compared to other CNNs developed for the same problem.[2]

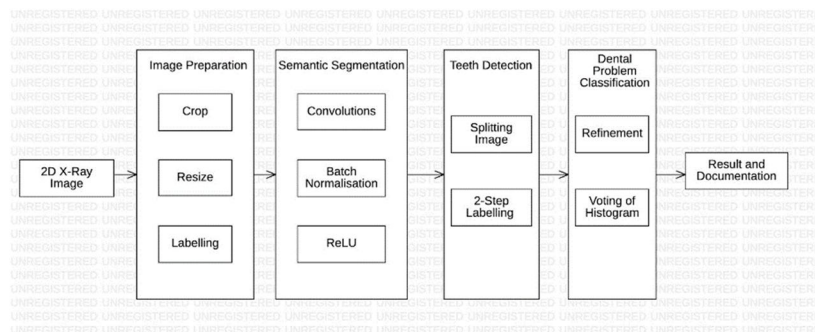


Figure 1: Architecture of the proposed model

Figure 1 depicts the architecture of the system. The purpose of a panoramic dental X-ray is to aid in the identification of disorders related to the jaw by providing a clear and comprehensive image of the whole upper and lower jaw, including the teeth and alveolar bone, in a single frame. The status of the periodontal soft tissue, tooth's roots, and alveolar bone, as well as the angle at which the teeth are tilted, may all be determined with pinpoint accuracy using panoramic photographs. Diagnosis, evaluation, and planning for surgery, as well as what comes after, are all preoperative procedures. assessment may all benefit from precise measurements of internal dental organs using anatomical pictures.[3]

A. Motivation and Contribution

Inflammation and infections harboured by bacteria in the mouth have been linked to several autoimmune and chronic disorders. Infections are sometimes difficult to detect, and their causes may be difficult to isolate, both of which can add significant time to the process of diagnosis. The diagnosis may vary, however, due to factors such as low imaging quality or weariness, fatigue. These all reasons can hinder the patient's treatment to a great extent. In acute cases this can also affect a patient's life. So, the medical team needs a technique for teeth recognition and dental issue categorization utilizing panoramic X-Ray pictures to help in reaching the accurate diagnosis. Our system will be using real-time x-ray, which has been verified by a dentist and belongs to patients with diseases ranging from chronic to acute cases. These x-rays help us in getting solutions for more classes as compared to the existing systems.

The paper is organized as follows: 2. Framework, 3. Proposed Solution 4. Experimental Results and 4. Conclusion and Future Scope.

II. FRAMEWORK

The two technologies that will form the basis of our system are deep learning and image processing. During the past several decades, Deep Learning has established itself as a very effective technology because of its capacity for handling enormous data sets. The use of hidden layers has become more common than other techniques, especially for pattern recognition. In deep learning, As one kind of deep neural network, Convolutional Neural Networks (CNNs) have widespread use.[1]

A. Convolutional Neural Network

Convolutional neural networks are composed of many layers of artificial neurons at each level. Synthetic neurons, also known as mathematical functions that calculate the weighted sum of a number of inputs and provide an activation value, are used in artificial intelligence, and are an approximate copy Convolutional neural networks are formed by stacking artificial neurons. By adding the weights of multiple inputs, mathematical functions known as "artificial neurons" generate an activation value. They facilitate the operation of artificial neural networks.[1][4]

B. U-net

An early version of the "totally convolutional network" that was proposed by Long, Shelhamer, and Darrell served as the basis for the development of the U-Net. [3] The fundamental idea is to expand a typical contracting network by include extra layers, with upsampling operators taking the place of pooling functions where applicable. These layers, as a consequence, contribute to an improvement in the resolution of the output. One or more successive convolutional layers will make use of the data in order to figure out how to produce correct outputs. [5]

C. Image Processing

The term "image processing" refers to the practice of applying various manipulations to a picture in the hopes of improving the quality of the image or extracting relevant data from it. In this kind of signal processing, a picture is used as input, and the result might be the same image or a subset of its features. Image processing mainly contains the following steps:

- Image processing and analysis.
- Image or report that may be modified depending on the examination of an input picture.[1]

III. PROPOSED SOLUTION

A. Image Preparation

During picture preparation, the image is improved so that it best meets the needs of the project. All identifying information, including names and phone numbers, are taken out of the photograph before it is processed further (patient ID, image number etc). Then, we reduce the pixel count such that each picture is only 2048 by 1024. It's common practice to rename radiographs and make new labels to go along with them. Problems with teeth may be labeled with a number from 0 to 13. [1] [7] The dataset used for our system includes real-time x-ray of patients. These x-rays have been verified by the dentist.



Figure2: Cropped Radiography image

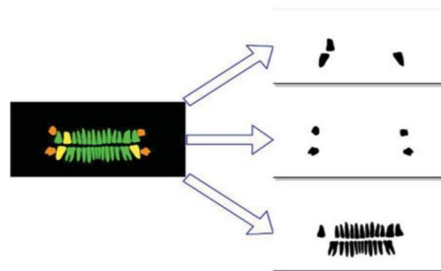


Figure 3: Teeth segmentation based on binarization process and semantic classes

B. Semantic Segmentation

Using the ERFNet neural network model, X-ray radiographs were semantically segmented. It's meant to stand in for a convolutional neural network that can do semantic segmentation in real time. The neural network has a 23-

layer encoder-decoder design. The first 16 layers make up the encoder, while the latter 7 are used for decoding.[8] The Batch Normalization method is used in the convolutional neural network to boost its efficiency, effectiveness, and robustness. Relying on four 1D convolutions with ReLU as activation function, the ERFNet rewrote the non-bottleneck architecture. An updated residual design, dubbed non-bottleneck-1D, improves the performance of neural networks. The first step in extracting features from a picture is to downscale the image. By combining the results of a single 3x3 convolution with a Max Pooling module's parallel output, the down sampler block accomplishes down sampling. ReLU is employed as the activation function. In order to recreate the original picture after feature extraction is complete, feature maps must be used. [9]

C. Tooth Detection

The initial stage in this procedure is to divide the original segmented picture into as many images as there are classes, with each image including only teeth belonging to the same semantic class. By setting the threshold to the color that represents the picture's semantic class, we may convert the image into a binary format. By using the erosion process, we were able to disentangle elements that had been joined by sharp, unwelcome edges. [10] Finally, numerical labels are extracted from each object in each binary image using a two-stage labeling process. The label images are utilised to determine the location of each affected tooth or dental problem in each case. The minimum and maximum pixel coordinates for each label are used as a starting point to calculate the bounding boxes.[11]

D. Dental Problem Classification

All identified bounding boxes are reevaluated in the refining stage. In this programme, we eliminate all the boxes with an area of less than 600 pixels. As soon as a tooth is recognised, a histogram is created with a length equal to the total number of semantic categories. For each semantic category, a vote is cast at the histogram node that best represents it. [1] As a result, we use an iterative process to move along the histogram until we reach the location occupied by the semantic class with the most votes in the area of interest. The teeth in the upper jaw come first in the sequence of numbers, followed by those in the lower jaw. To keep things simple, we'll be counting from left to right. All the non-background semantic segmentation picture pixels are horizontally projected for jaw separation. [12].

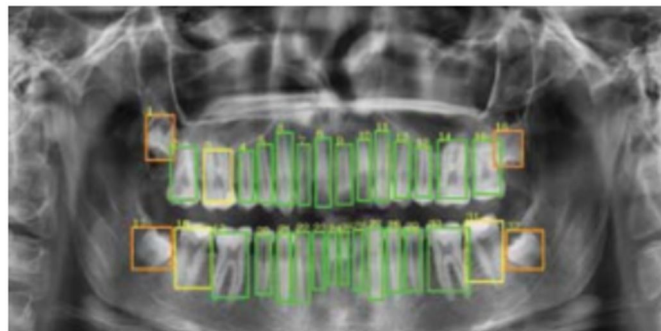


Figure 4: Proposed solution's result

IV. EXPERIMENTAL RESULTS

In this portion of the study, we assess the effectiveness of the suggested approach based on two criteria: precision and the degree to which intersections dominate unions. Finally, the proposed therapy is compared to others that have been used for the same oral issues. We ran our tests using a machine with a 2.60 GHz Intel i7-4720HQ CPU and an NVIDIA GeForce 950M GPU. In addition to being written in Python, the solution makes no use of hardware acceleration techniques.

For starters, the doctor will take a standard 2D x-ray. First steps will be taken to ensure the picture meets all criteria. As a result, this is the result, where each tooth can be examined separately.

V. CONCLUSION AND FUTURE SCOPE

In this study, we introduced a unique technique for making use of panoramic dental radiographs for the diagnosis and categorization of dental issues. Pixel-by-pixel annotations were applied to images collected from three dental practises. To indicate 20 various issues that might influence teeth, allowing for the required outcomes to be

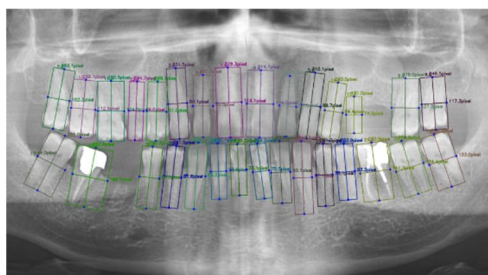


Figure 5: Final output

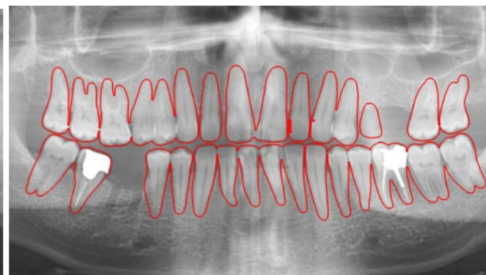


Figure 6: Problem detection

obtained. The annotated data was enhanced by a number of processes. In addition, a Convolutional neural network was trained to do semantic segmentation using data from the photos. [14] The pictures were then binarized using the two-stage labeling technique and numerous thresholds. Using this strategy, we were able to identify every single occurrence of teeth. Each tooth or set of teeth is assigned a number, and a report detailing the dental problems for each tooth or set of teeth is created. When a medical professional needs help making a diagnosis, they might construct an instance to use as a guide. Many criteria are used to evaluate the produced solution and compare it to other comparable algorithms.[15]

The future success of the suggested solution depends on our ability to speed up its execution using hardware acceleration techniques. One potential shortcoming of our topologies is that learning may stall in the intermediate layers of deeper models, increasing the possibility that the network could eventually come to disregard those levels entirely. [18] We also want to improve the suggested solution's accuracy and add additional semantic classifications. Dental work with exceedingly deep difficulties is challenging, yet it is possible with improved technology.[19].

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