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Neural Network-Based Detection of Dental Caries Using Roboflow and Jetson Nano

***Abstract*—This study developed a convolutional neural network for the automated detection of dental conditions—specifically caries, restorations, root canals, and prostheses—on radiographic images using the Roboflow platform and deployed on the NVIDIA Jetson Nano. A dataset of 1,933 dental X-ray images, provided by the Bright Smile clinic and expanded to 4,639 through data augmentation techniques, was used. The model was trained and tested in five iterative versions, gradually incorporating each dental condition class. Preprocessing techniques, including a 20% increase in image saturation and targeted augmentations, significantly improved detection performance. The final model achieved a mean Average Precision (mAP) of 97.7%, with notable improvement in the identification of dental caries—previously the most challenging class. These results demonstrate that optimized preprocessing combined with YOLO-based training in Roboflow and deployment on Jetson Nano constitutes an effective pipeline for real-time dental diagnostics.**

***Index Terms*—Caries, X-Rays, Convolutional Neural Network, Nvidia Jetson Nano, Dental Problems, Roboflow.**

I. Introduction

The integration of artificial intelligence (AI) has transformed healthcare diagnostics, particularly in image-based fields like dentistry. Early detection of dental caries is vital to prevent complications such as pain, infection, and tooth loss. AI-powered object detection models, especially convolutional neural networks (CNNs), can enhance radiograph interpretation by recognizing patterns that may be missed by the human eye.

Dental caries is a major global health issue affecting people of all ages, from children to adults, impacting quality of life and requiring significant resources for prevention and treatment. Complications include pain, sensitivity, difficulty eating, infections, and even systemic health issues if left untreated [1].

This project aims to develop an automated caries detection system using CNNs trained on labeled dental radiographs, with deployment on an NVIDIA Jetson Nano for portable, real-time diagnostics. Roboflow will be used for dataset preparation, offering effective data labeling and image processing tools essential for building accurate neural networks.

II. Context

Numerous studies have explored AI in dental diagnostics, showing promising results in classifying and segmenting oral conditions. This chapter presents examples relevant to the topic, highlighting the role of neural networks in dentistry. Despite challenges, AI in medicine has proven effective, with growing accuracy and reliability driving its integration into diagnostics and treatment.

A study on caries recognition used 834 radiographs from 100 patients at King Abdulaziz University Hospital: 583 for training, 167 for validation, and 84 for testing. Results showed that higher image detail improved AI's diagnostic accuracy [2].

The COCO model demonstrates that models can achieve high accuracy in object identification, with better dataset preparation and more training images enhancing learning effectiveness [3].

Roboflow performed in real-world scenarios with varied backgrounds and lighting conditions [4]. Analysis showed individual count errors averaging 3.64, 3.68, and 3.88, indicating consistent difficulty across tasks.

Krippendorff Alpha was found to be 0.76, reflecting good agreement among participants. Low scores would suggest disagreement or poor data labeling, underscoring the importance of accurately labeling and classifying each image [5].

Applying these models to Raspberry Pi-based stations remains future work to address current challenges [6].

AI learning often uses public sensor data corrected through neural networks. Studies show that inaccuracies from low-cost air quality sensors can be mitigated with ANN models. MobileNetV2 achieved consistent results on a Raspberry Pi 3 B+, with 0.87 accuracy, 0.863 F1 score, 0.933 specificity, and 0.87 precision.

Considering hardware, using a Jetson Nano for detecting cavities in radiographs is promising given its superior processing capacity over Raspberry Pi, with recognition rates of 0.98 in robotic path detection. This makes it efficient and suitable for rapid medical image processing [7].

For neural network training on radiographic images, it's essential to collect and label examples of both healthy and damaged teeth to improve YOLO-based model accuracy. Though training can be resource-intensive, using processors designed for such tasks helps manage workload effectively [8].

A. Dental Caries

Dental caries are damage to tooth structure caused by bacteria that feed on food particles, especially sugars, producing acids that form plaque adhering to teeth, typically on the last molars [9]. Key factors analyzed include lifestyle, diet, government support in dental health, availability of clinics, and preventive measures.

B. Classification of Caries According to Black

Caries are classified by location and severity following Greene Vardiman Black: Class I: On molars/premolars chewing surfaces, where brushing is difficult. Class II: Between

12 molar and premolar teeth due to cleaning challenges. Class III: On the sides of incisors and canines. Class IV: On the upper part of incisors and canines. Class V: Near the gums in hard-to-reach areas. This classification provides a clear framework for analyzing cases [10].

C. *Dental Radiographs*

Radiographs are valuable for diagnosis by revealing internal details not visible to the naked eye, as shown in Fig. 1 [11].

Fig. 1. Caries shape on a premolar radiograph.

D. *Aspects by Grade*

Untreated cavities progressively damage teeth. Severity levels are shown in Fig. 2 [12, 13]: • Code 0: Sound tooth surface.
17 • Codes 1–2: Initial stage (early enamel lesions). • Codes 3–4: Moderate stage (localized breakdown or dentin shadow). • Codes 5–6: Extensive stage (visible cavitation with dentin).

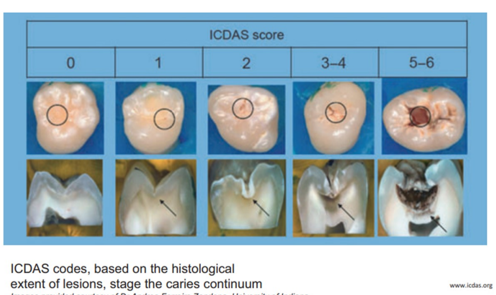

Fig. 2. Grades of Caries

E. *Deep Learning for Object Detection*

Deep learning methods are widely used in smart manufacturing for automating defect detection, component identification, and process monitoring, enhancing system responsiveness [14].

F. *Customized Object Detection Models*

Research aims to develop industrial object detection models that need less training data while maintaining high performance, which is valuable when data collection is difficult [15].

G. *Jetson Nano*

Jetson Nano is a small yet powerful AI computer for embedded and IoT applications. It has a 40-pin header for peripheral connections and uses the Jetson GPIO Python library for control. Supporting frameworks like TensorFlow, PyTorch, and Keras, Jetson Nano is more than a scaled-down NVIDIA board, making it a flexible AI platform [16].

H. *Roboflow*

Roboflow enables developers of all levels to create computer vision applications more easily by streamlining data labeling and model training. Launched in 2020 to simplify dataset preparation, it supports converting between annotation formats, reducing the need for custom scripts and letting developers focus on building models [17].

III. Methology

In this project an incremental approach is used as shown in Fig. 3 [18]. Since what will be done will be testing and training in stages where we will individually train different versions of the neural network, where they will evaluate one class per version to analyze which of these classes is best detected by the model for object detection that Roboflow provides us.

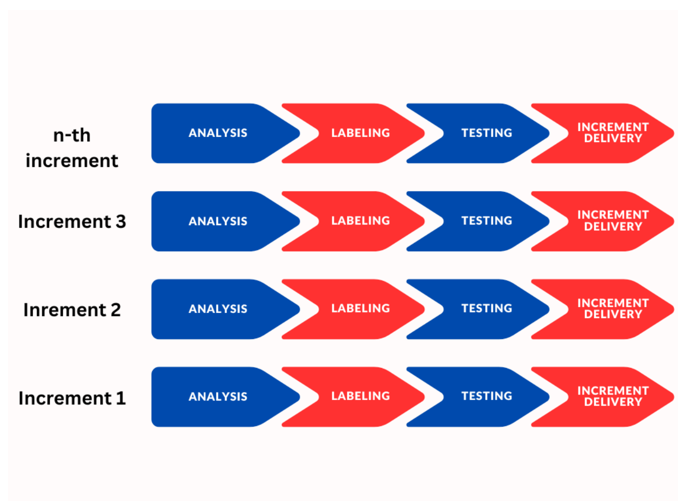

Fig. 3. Methology Increment

A. *Tools that were used*

- balenaEtcher: With this free and open-source tool, which allows writing image files (.iso and.img formats) and compressed folders to storage media, you may create bespoke SD memory cards and USB flash drives. Distributing and using it is governed under the Apache License 2.0, which Balena wrote.
- Jetson Nano Developer kit: The Jetson Nano Development Kit will be the vehicle for JetPack implementation. Based on the Ubuntu Linux operating system, JetPack offers a very specialised and effective environment for creating artificial intelligence applications.

- Roboflow: A website that simplifies computer vision data management and preprocessing, will receive the images gathered for each identification challenge. For every one of the particular types plugs, prostheses, cavities, root canal restorations, images will be tagged using Roboflow annotation tools. Also, Roboflow will enable the construction of ideal data sets, which will include techniques for data augmentation and preprocessing to improve the caliber of neural network training.

B. Study Methology

- Plug recognition: The neural network will be trained to identify and classify dental and medical plugs based on their unique visual features.
- Prosthesis recognition: The model will detect various prostheses (e.g., dental implants, joint replacements), focusing on structural and compositional traits for accurate identification.
- Root canal restorations: The network will learn to recognize endodontic repairs in radiographs, identifying features like closure quality and potential complications to support diagnosis and treatment planning.
- Caries detection: The model will be trained to detect early-stage dental caries by analyzing density and texture variations in enamel from dental images, aiding in preventive diagnostics.

IV. Results

A. Training and Testing

1) Restoration: In the first instance, it had proceeded to train a version of the convolutional neural network, which was specifically designed to carry out the automatic detection of restorations in medical radiographs. The training process shown in Fig. 4, labeled approximately 807 restorations, significantly enhancing the model's accuracy in identifying these structures in the radiological images and the training, valid and test images were distributed between 70, 20 and 10 percent respectively for the network to train and we will take these default values for all networks.

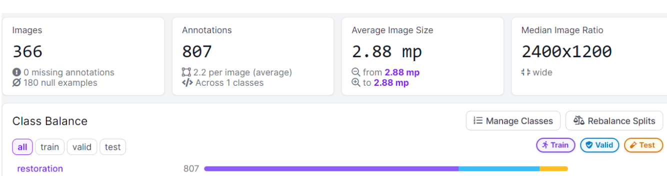

Fig. 4. Amount of Labels of the 1st Version

At the end of the training, the following results were obtained in the first stage of the training, which only focused on the detection of the caps on the teeth in the radiographs, thus obtaining a mAP of 62.5 percent as shown in Fig 5.

The first version of the neural network was tested just to observe its performance, and it was easy to predict what the restorations would be. It can be observed in Fig. 6, that here the neural network comes to confuse some braces as restorations in this first version.

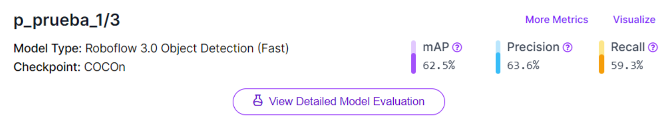

Fig. 5. mAP of the 1st Version

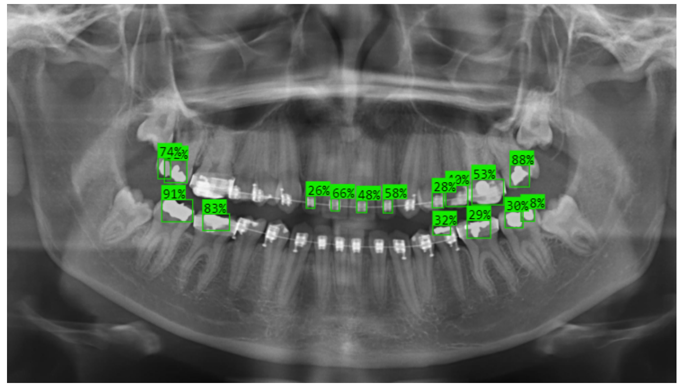

Fig. 6. Object Detection: Restoration

2) Root Canal: This second version was trained to observe how the Roboflow model can recognize the root canals and thus incorporate the first version, which only detected the restorations and now may also recognize the root canals. They were labeled 702 root canals, so these same ones will be added to the first version. Since the training of this version was completed, the results obtained were better than the previous ones, since the MAP was increased by adding these other classes to improve the neural network as shown in Fig. 7, is prepared, which would be to add the prostheses to see if the MAP also increases.

Fig. 7. Amount of Labels of the 2nd Version

As we can see in Fig. 8 and Fig. 9, it can be seen that the incorporation of the Root channel class was successfully achieved, Despite the fact that almost some of them are not seen at all, the neural network managed to adapt well to not only learn how a root channel is viewed, but also improved the mAP to a 70.1%

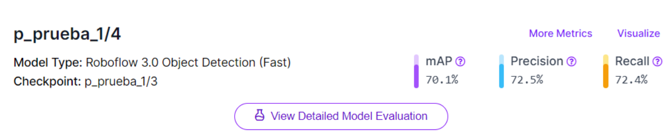

Fig. 8. mAP of 2nd Version

3) Prothesis: In order to determine how well the neural network will detect the prosthesis, we are now including them

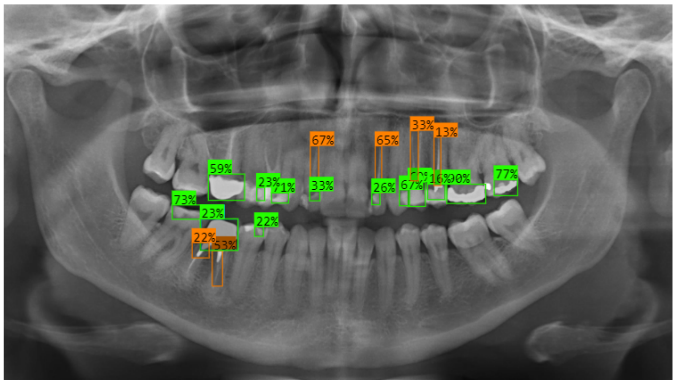

Fig. 9. Object Detection: Restoration and Root Canal

into the network together with the other two classes that came before it. About 529 prostheses were labeled on the radiographs Fig. 10.

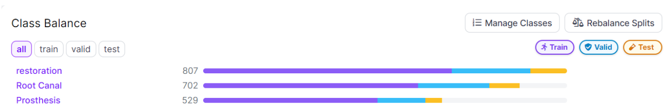

Fig. 10. Amount of Labels of the 3rd Version

We can see the Mean Average Precision (mAP) in Fig. 11, did not rise much at the conclusion of this version's training. This result is probably the consequence of the dataset lacking sufficient instances for the network to learn how to recognize prostheses in addition to other classes like restorations and root canals. Perhaps the network was unable to generalize successfully to these items because of the small amount of representation. Multiple classes further increased complexity and forced the network to distinguish between slightly different characteristics, which further reduced the total mAP increase.

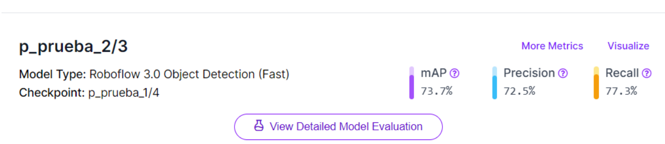

Fig. 11. mAP of the 3rd Version

Although the mAP may not have increased much as shown in Fig. 12, it was only 73.7 percent. The model recognizes and differentiates between what is a prosthesis and what is a restoration without getting confused. It is expected that the next stage will be better than this one.

4) Cavities: About 781 caries were labeled on the radiographs. Also, what was done was to place more examples of prostheses and root canals in such a way that the balance between the classes was balanced so as to expect optimal results from the mAP as shown in Fig. 13.

When trying to have a balanced number among the classes, what would be the mAP decreased enormously, seeing this

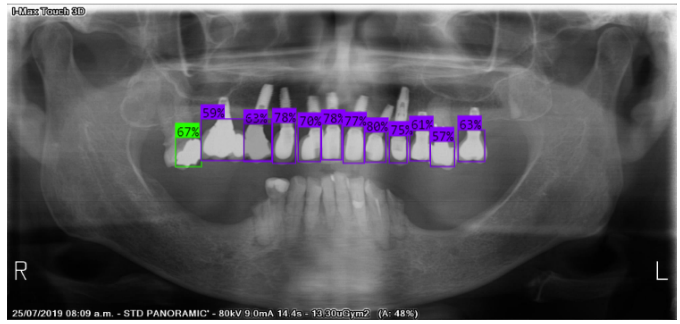

Fig. 12. Object Detection: Restoration and Prothesis

Fig. 13. Amount of Labels of the 4th Version

panorama we can say that the cavities in the radiographs are not detected correctly, since the model that RoboFlow has for object detection has difficulties in recognizing them Fig. 14.

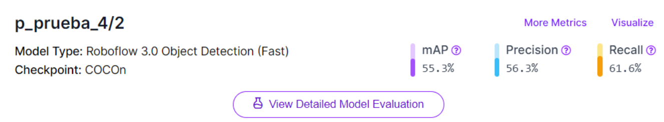

Fig. 14. mAP of the 4th Version

It is confirmed that by testing the cavities in this latest version of the neural network, it is almost not difficult to recognize what would be a cavity in an X-ray. If in itself it is difficult for the human eye to see what would be a cavity, it was expected that the model would have the same difficulties.

It can only recognize large cavities since it would not be able to detect small ones correctly as shown in Fig. 15, the initial processing of the images would have to be improved so that when labeling and training the neural network it would be easier to recognize the other classes, especially the cavities that are the main focus of this project.

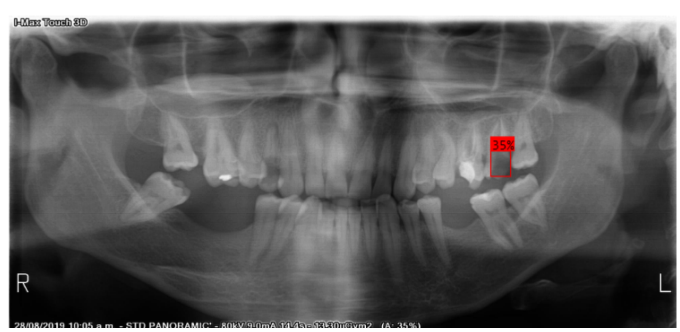

Fig. 15. Object Detection: Cavity

The image samples were to be relabeled, and the distribution of the train, valid, and test images changed and still did not pass more than 63 percent.

B. Optimizing Labeling and The Object Detection

At this point, it was concluded that in order for the cavities and the other classes in the Roboflow model to have optimal recognition and training in the examples that are placed, in Fig. 16, the saturation of the images will have to be increased to 20 percent to make it easier to see where the cavities are.

Fig. 16. Saturated Radiograph at 20 percent

A final version was created in which the same images were labeled again, but this time with a saturation of 20 percent. The number of labels is the same as the 4th version in Figure 17. There were 809 restorations, 808 root canals, 781 caries, and 759 prostheses, respectively.

In the end, optimal results were obtained as expected, by saturating the images, as shown in Fig. 17, the mAP of this version of the neural network improved significantly, reaching 89.9 percent, almost 90 percent, it is planned that by entering more augmentations the training and ultimately the recognition of this neural network will improve even more. For the next and final version, more augmentations will be added to further improve the MAP.

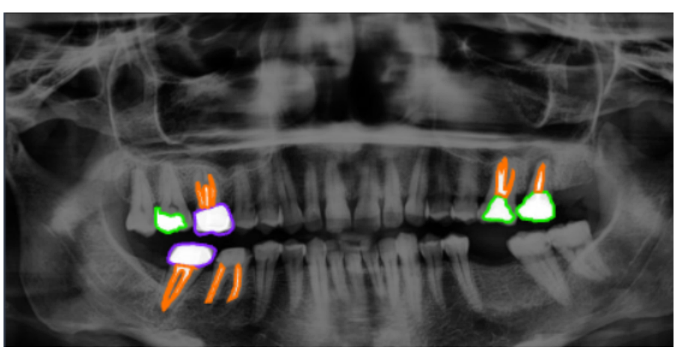

Fig. 17. Relabeling Saturated Images

For this latest version, they were added the following augmentations, Fig. 18:

Finally, it achieved a mAP of 97.7 percent by placing these augmentations, thus obtaining an optimal neural network for caries recognition along with the other classes to serve as an auxiliary tool for the area of dentistry presented in Fig. 19:

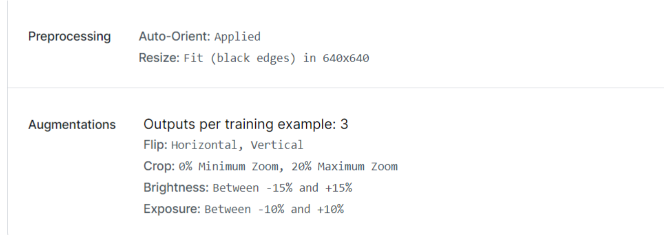

Fig. 18. Augmentations Added

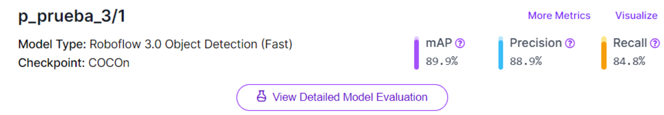

Fig. 19. mAP of the 5th Version

The following figure Fig. 20, illustrates the performance of the model. It demonstrates that saturating the images led to more efficient class detection, with a particularly notable improvement in caries detection. By enhancing the color saturation, the network was able to better distinguish between different features, making it easier to identify and classify the objects within the images. This adjustment in the preprocessing stage helped in highlighting the contrasts and details necessary for accurate detection, thus improving the model's overall performance.

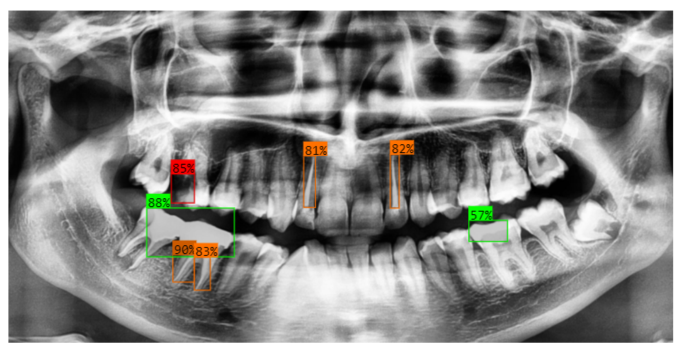

Fig. 20. Object Detection: Final Version

V. Conclusions

This research found that the RoboFlow model could more easily detect restorations, prostheses and root canals than cavities due to the subtle grey-scale variations that make cavities more difficult to distinguish. Despite multiple parameter adjustments, early model versions performed at less than 63% accuracy, partly due to insufficiently labelled training data.

A key improvement was increasing image saturation by 20%, which enhanced contrast and made cavities more visible, thereby reducing confusion with tooth shadows. Furthermore, applying augmentation techniques such as brightness and contrast adjustments, as well as other transformations, expanded the dataset from 1,933 to 4,639 images. This greater variety improved the model's generalisation and detection accuracy, resulting in a high mAP score.

For future research using RoboFlow with radiographs, it is recommended that image saturation and augmentation techniques are applied, and that object contours are carefully labelled to improve detection precision and reduce misclassification.

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