DENTAL CARIES DETECTION USING DEEP LEARNING

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This is to certify that Dissertation Report entitled "**DENTAL CARIES DETECTION USING DEEP LEARNING"** submitted by **CATHERINE NEMBIAKCHING (20103057), DANIEL LUNGINLIAN (20103046), RAMAVATH VINOD NAIK (20103045)** to National Institute of Technology Manipur, Imphal, Manipur (India), is a record carried out by them under the supervision of **MR. SANABAM BINESHWOR SINGH,** and is worthy of consideration for the award of the degree of **BACHELOR OF TECHNOLOGY (B.TECH.)** in **COMPUTER SCIENCE AND ENGINEERING DEPARTMENT** of the institute.

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DECLARATION

We declare and certify that

- The work contained in this thesis is original and has been done by us and the general supervision of my supervisor.

- The work has not been submitted to any other institute for any degree or diploma.

- Whenever I have used materials (data, theoretical analysis, results) from other sources, I have given due credit to them by citing them in the text of the thesis and giving their details in the references.

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ABSTRACT

This study explores the application of deep learning for detecting dental caries using X-ray images, aiming to enhance the accuracy and efficiency of traditional diagnostic methods. We developed a model based on YOLOv8, a state-of-the-art convolutional neural network (CNN) architecture, trained on annotated dental X-ray images to automatically identify and localize carious lesions. The model incorporates multiple convolutional layers for feature extraction and fully connected layers for classification, with data augmentation techniques employed to improve robustness. Evaluation metrics such as accuracy, sensitivity, confusion matrix, precision curve, recall curve, and F1 score demonstrated that our model achieves high accuracy and reliability, outperforming traditional methods. These results suggest that deep learning, specifically utilizing YOLOv8, can significantly improve dental diagnostics by offering a non-invasive, efficient, and reliable method for caries detection. Future work will focus on dataset expansion, advanced image processing, and clinical validation to further enhance the model's applicability.

LIST OF FIGURES

TABLE OF CONTENTS

CHAPTER 1
INTRODUCTION

Machine learning, a subset of artificial intelligence, enables systems to learn and improve through data-driven experiences, devoid of explicit programming. Its various approaches—supervised, unsupervised, and reinforcement learning—provide diverse methodologies for learning from data, be it labelled or unlabelled.

This report focuses on the application of deep learning, a subset of machine learning, specifically in the realm of dental care—more precisely, the accurate detection of dental caries in oral images. Emphasizing the pivotal role of early detection in oral health, this exploration aims to harness deep learning's potential to enhance diagnostic precision and enable timely interventions.

By delving into the intricate workings of convolutional neural networks (CNNs) and their adaptation for dental caries detection, this report aims to showcase how cutting-edge technology can transform traditional diagnostic methods. Its core objective lies not only in identifying but in proactively recognizing dental caries, ultimately contributing to improved oral health care practices. This report strives to highlight the transformative impact of deploying advanced computational models in revolutionizing dental diagnostics for better patient outcomes.

For easier segmentation and detection of dental caries, prior knowledge for several tasks is needed. There is a need to understand the various sections of the tooth and the specific position of the lesion on the tooth. An understanding of the types of dental images to be used, for instance, panoramic or bitewing radiographs, is also needed. Furthermore, the specific regions or areas of interest which are required should be clear in order to be able to choose the suitable method for segmentation and detection of caries. All this information is required in order to achieve high performance segmentation and detection of dental caries.

1.1Tooth Anatomy

The tooth is a small white structure found in the jawbone of animals and human beings. In human beings, the number of teeth ranges from 20 primary teeth in children to 28–32 permanent teeth in adults. Further, the tooth can be broken down into three main layers: the crown, neck, and root. The crown is the visible region above the gum line. The neck connects the crown to the root, while the root is the region inside the bone socket. Additionally, each tooth consists of hard tissues that protect the soft tissues in the center, as can be seen in Figure 1.

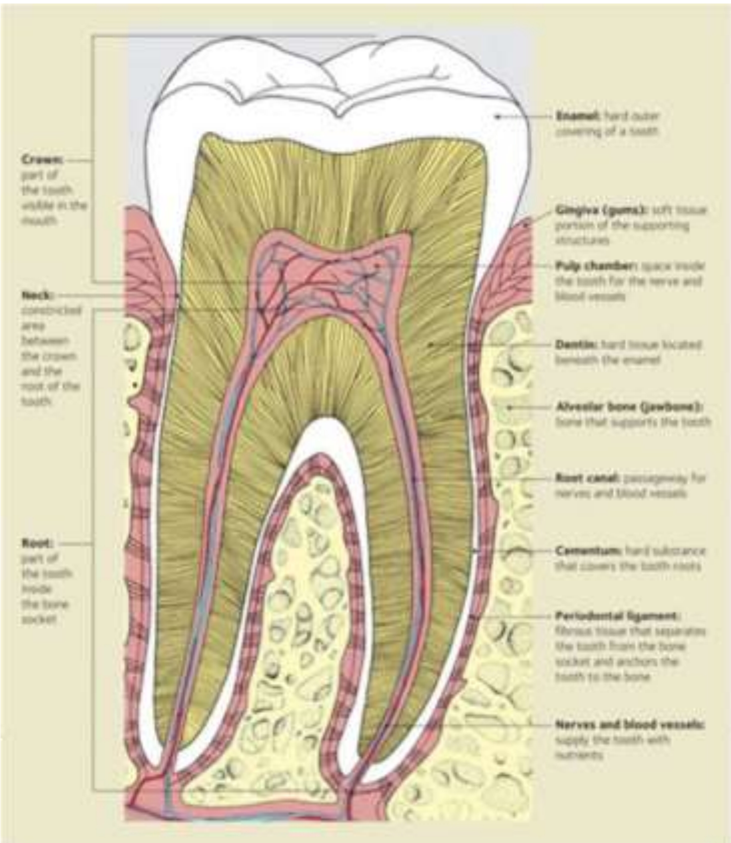

Fig. 1: Cross section of a molar tooth

1.2. Dental Caries

Dental caries is a tooth infection caused by bacteria. Diet that includes fructose, sucrose, and glucose accelerates the occurrence of dental caries. The acid released from the above process leads to demineralization of the tooth surface. Caries occurs when the rate of demineralization is less than the rate of decay. There are various categories of dental caries and these can be characterized. The protocol characterizes dental caries based on its location and also the affected tooth. The categories are as follows:

Class I: dental caries on occlusal surfaces of posterior teeth, for instance, molars and incisors.

Class II: occurs on proximal surfaces of posterior teeth.

Class III: occurs on interproximal surfaces of anterior teeth, with no incisor edge involvement.

Class IV: occurs on interproximal surfaces of anterior teeth with incisor edge involvement.

Class V: occurs on the lingual or cervical third of the facial surface of the tooth.

Class VI: occurs on the occlusal or incisor edge, worn away due to attrition.

From positional classification, caries can also be classified based on the severity of lesions on the tooth. This is done based on the amount of dentin and enamel that has been affected by the caries.

Incipient caries are caries that have a depth of less than half of the enamel of the tooth.

Moderate caries are caries that are more than halfway through the enamel but do not touch the dentin.

Advanced caries are caries that extend to the dentin region.

Severe caries are caries that extend more than halfway through the dentin and even reach the pulp.

Identification of caries under classes I, IV, and VI can be done during clinical inspection, since the regions are visible orally. The introduction of X-rays in the medical field has greatly improved diagnosis of various ailments. In the dental field, radiography has improved the visual inspection of patient's teeth. X-rays have enabled professionals to be able to view previously unobservable regions of caries that would have gone untreated.

1.3. Dental Radiographs: X-Rays

There are varying degrees of information needed depending on the form of treatment required to diagnose a certain ailment. An X-ray or radiograph is a digital film that represents unobservable information not visible by the naked eye. Figures 2–4 show some types of radiographs. There are two types of radiographs, intraoral and extraoral.

Intraoral radiographs: X-ray film captures radiographic images while inside the mouth. This type is subdivided further into bitewing radiographs, periapical radiographs, and occlusal radiographs.

Extraoral radiographs: X-ray film captures radiographic images while outside the mouth. This type is subdivided further into panoramic radiograph, computed tomography (CT), and sialography.

Fig. 2: Periapical radiograph.

Fig. 3: Bitewing radiograph.

Fig. 4: Panoramic radiograph.

1.4: Dental Image Segmentation Methods

Image segmentation plays a crucial role in many medical imaging applications by automating or facilitating the delineation of anatomical structure or other regions of interest. The categories of dental segmentation methods are categorized according to various characteristics such as region, entropy, shape, threshold, and pixels correlation among others. These characteristics were from thermal, X-ray images to aid analysis of specific points or regions of interest. Dental image segmentation is classified as region-based, cluster-based, threshold-based, boundary-based, and watershed-based methods.

1.4.1: Threshold-Based

These methods are among the simplest methods used for segmentation. Threshold based image segmentation techniques discriminate regions on the basis of intensity value difference between pixels. The pixels in the image are classified into two classes based on some predefined threshold value. Threshold for image segmentation has been calculated based on maximum entropy, interclass variation or histogram. Threshold based segmentation does not account for spatial characteristics of an image, making it sensitive to noise and intensity in homogeneities. The threshold-based segmentation techniques perform well for images which have only two components; for complex images, these methods are often used as an initial step in a sequence of image processing operations.

1.4.2 Region-Based

The idea of region-based algorithms comes from the observation that pixels inside a structure tend to have similar intensities. Region growing techniques are used to segment regions based on 12 some similarity criteria. Each region of interest (ROI) requires its own seed initialization, after selecting the initial seeds, algorithm searches for the neighborhood pixels which have intensities within a predefined interval. To eliminate the need for manual seed initialization, some algorithms used the statistical information and a prior knowledge of the ROIs to select the seeds semi automatically or fully automatically. The drawbacks of these methods are that they are sensitive to the seed selection and also sensitive to the noise, sometimes the similarity criterion is not exactly defined, also the algorithm mainly relies on the image intensity information. In addition, these techniques are dominated by the growth of the current region. Region growing methods are simple techniques that provide good results especially with smaller region segmentation once all mentioned challenges are properly addressed.

1.4.3 Cluster-Based

It is the automatic grouping of image data based on certain degrees of similarity between the data. The degree of similarity depends on the problem being solved. The algorithm used to perform clustering of data uses the automatically detected groups as initial parameters.

1.4.4 Boundary-Based

It is used to find edge or point discontinuities on images. It detects color or pixel intensity discontinuities in the gray levels of the image. Active contours are used as one of the approaches to segment images based on their boundaries. The approach performs segmentation by outlining an object from an image and is also referred to as the snake method. Level set method (LSM) is another approach for detecting boundaries in an image. It handles segmentation by performing geometric operations to detect contours with topology changes.

1.4.5 Watershed-based

It is performed on a grayscale image and used mathematical morphology to segment adjacent regions in an image; watershed-based segmentation was used on bitewing dental radiographs. It was also used as a combination of the K-means clustering and the watershed method for color-based segmentation.

CHAPTER 2
MOTIVATION AND OBJECTIVE

2.1 Motivation

Global Impact of Dental Caries

- Dental caries is a widespread issue affecting people of all ages globally.
- The impact on oral health is profound, leading to discomfort, pain, and, if left untreated, more severe health complications.
- This project is motivated by the pressing need to address and mitigate the impact of dental caries on individuals and communities. Challenges in Traditional Approaches
- Traditional methods of dental caries detection often rely on manual inspection, which is subjective and time-consuming.
- The limitations of visual and tactile examinations pose challenges, particularly in identifying early-stage or subtle caries.
- This project aims to overcome these limitations through the application of advanced technology.

2.2 Objective

Objective Statement: "Our primary goal is to leverage the power of deep learning to create an intelligent system that can accurately and efficiently detect dental caries in oral images".

Importance of Early Detection: Emphasize the significance of early detection in preventing the progression of dental caries, leading to better patient outcomes and reduced treatment costs.

Enhancing Diagnostic Precision: Discuss how the project aims to enhance diagnostic precision by automating the identification of carious lesions, reducing the reliance on manual examination, and potentially catching subtle or early-stage caries that may be overlooked.

2.3 Summary

In this chapter, we have discussed about our main motive towards selecting this topic for our project work and also discussed about our objectives in this project.

CHAPTER 3
LITERATURE SURVEY

Andras Horvath et al. (2019) proposed CNN architectures (subpixel network and U-net) for enhancing 2D cone-beam CT image resolution of ex vivo teeth, outperforming reconstruction-based super-resolution methods [6]. Abdolvahab Ehsani Rad et al. (2018) introduced a segmentation methodology using morphological data and neural networks for efficient tooth segmentation, achieving a high detection accuracy of 98% [7].

Nima Karimian et al. (2018) applied deep CNNs to oral tissue classification in OCT imaging, demonstrating its effectiveness in identifying tissue densities [8]. Olaf Ronneberger et al. (2015) presented a U-shaped CNN model for automatic dental X-ray segmentation with high accuracy in identifying enamel, dentin, and pulp [9].

Angelino et al. (2017) developed a near-infrared diode imaging system for detecting teeth decay, albeit with accuracy limitations [10]. Joonhyang Choi et al. (2018) reported an automated decay detection system using CNNs and refinement modules, achieving early-stage decay identification [11].

Shashikant Patil et al. (2019) utilized AI techniques for decay detection, emphasizing the effectiveness of science and neural network algorithms [12]. Laura A Zanell Calzada et al. (2018) proposed a dense artificial neural network for classifying dental subjects, achieving significant accuracy in distinguishing decay presence from absence [13].

Casalegno et al. (2019) employed a CNN for machine-controlled detection and localization of dental lesions, demonstrating promising results for tooth decay detection [14]. Prajapati et al. (2017) explored CNNs for dental disease classification with encouraging accuracy using a small labeled dataset [15].

Geetha et al. (2020) developed a diagnostic system using neural networks achieving 97.1% accuracy in tooth decay diagnosis [16]. Moutselos et al. (2019) utilized Mask R-CNN to detect decay on occlusal surfaces across a 7-class scale, discussing potential improvements for better classification [17].

This concise literature overview highlights diverse methodologies leveraging deep learning, CNNs, and imaging techniques for dental caries detection, emphasizing varying levels of success, limitations, and potential enhancements across multiple studies

CHAPTER 4
DEEP LEARNING

Deep learning is a machine learning algorithm that uses artificial neural networks to teach computers to process data in a way that mimics the human brain. Deep learning models can recognize complex patterns in data to produce accurate insights and predictions.

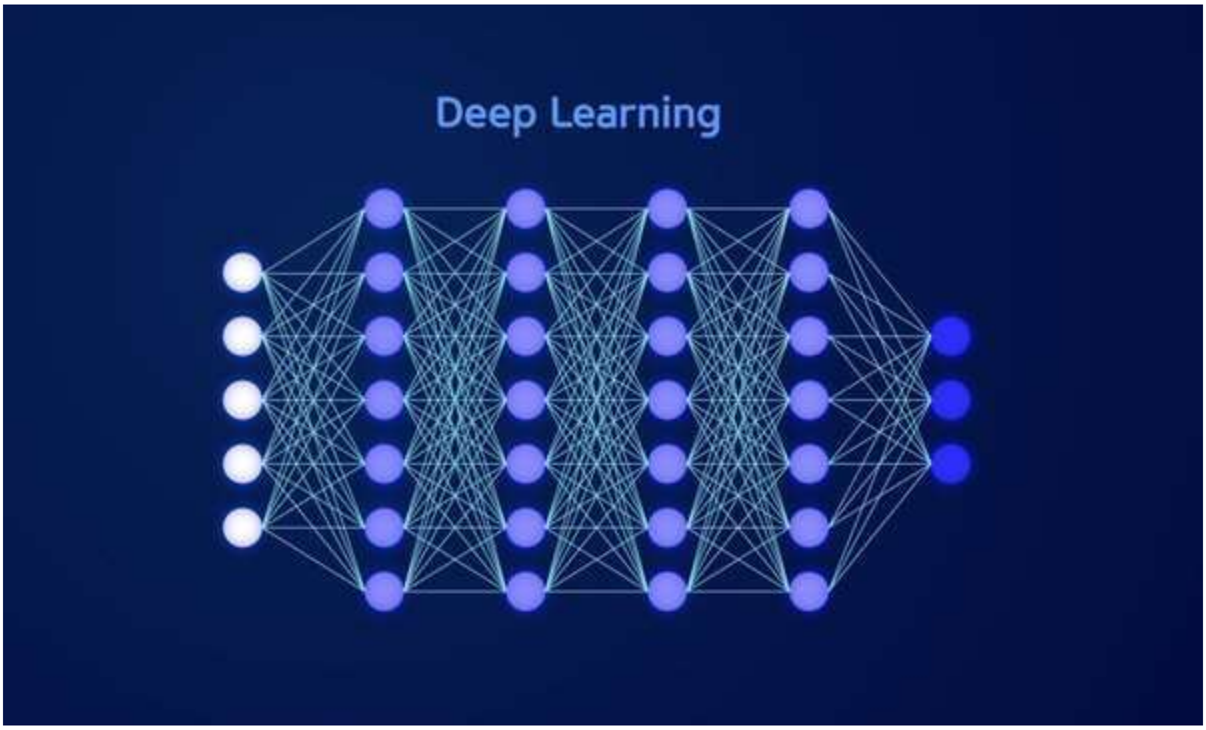

Fig. 5: Deep Learning Blockchain Neural Network.

Deep learning, with two major models—Massive-Training Artificial Neural Networks(MTANNs) and Convolutional Neural Networks (CNNs)—uses network structures con-sisting of multiple layers for automatically learning and self-learning backpropagation.

Deep learning with image input has been explosively growing and promising to become an important platform in medical images. One of its most popular applications in the medical field is classification. Applications of deep learning in dentistry are remarkable in a variety of fields such as teeth-related diseases, dental plaque, and periodontium.

In terms of dental caries, currently, different approaches exist for building automatic diagnosis tools, such as the application of common data-mining algorithms on the factors from annual oral check-ups or the classification algorithms used two separate steps: image segmentation and classification. However, the current prominent approach is building an object detector via deep learning models, such as CNN, deep neural network (DNN),Region-Based CNN (R-CNN), Fast R-CNN, Faster R-CNN, Mask R-CNN, You Only LookOnce version 3 (YOLOv3), RetinaNet, and Single-Shot Multi-Box Detector (SSD).

Deep learning has proven especially powerful for the analysis of complex data, like imagery [8], and has been used for image classification (i.e., labeling the image, e.g., signs of disease are present), detection (e.g. signs of disease are present in this area, usually indicated by a bounding box), and segmentation (i.e., signs of disease are present on these specific pixels). The accuracy of deep learning for medical image analysis has been found to match or, in some cases, surpass that of experts. In dentistry, deep learning has been employed for image analysis in orthodontics, specifically landmark analysis on cephalometric radiographs, endodontics (detection of apical lesions), periodontology (periodontal bone loss) and cariology.

Dental caries is the most prevalent condition in the human population. Caries lesions can be detected by visual and tactile means, while often this visual-tactile detection is supplemented by imaging strategies like radiography (the most common type of adjunct detection method), optical coherence tomography, quantitative light-induced fluorescence, intraoral scanner, or near-infrared light transillumination. Evaluating any imagery for caries detection is a challenge for practitioners; dentists miss a substantial proportion of early caries lesions in radiographs but also other image types, and show considerable variability in their diagnostic findings and treatment decisions.

The usage of AI, specifically deep learning, may support practitioners in caries lesion detection and diagnosis on imagery. Notably, the development in the field of deep learning of caries detection is highly dynamic; moreover, studies show substantial variability in methods and outcomes.

CHAPTER 5
METHODOLOGY

The following sections outline the various stages of our proposed system for diagnosing dental caries:

- Data collection-A dataset comprising images of teeth, encompassing instances both with and without caries, was meticulously collected from diverse sources. This dataset formed the foundational element for model training and validation.
- Image Preprocessing-Prior to model training, a rigorous image preprocessing phase was undertaken to ensure compatibility with deep learning models. Techniques such as resizing, normalization, and data augmentation were employed to enhance image quality, consistency, and diversity within the dataset.
- Deep CNN Model Development-A customized deep CNN model architecture was meticulously designed, considering the intricacies of dental caries detection. This model was trained on the preprocessed dataset, fine-tuning its parameters to optimize performance and enhance its ability to discern subtle patterns indicative of dental caries.
- Model Evaluation-The performance of the developed deep CNN model was rigorously evaluated by comparing its predictions with ground truth labels. Evaluation metrics, including accuracy, precision, recall, and F1 score, were employed to assess the model's efficacy in accurately detecting dental caries within oral images.
- Visualization-A comprehensive diagram elucidating the dental caries detection process using the deep CNN model was created. This visualization aimed to articulate the methodology's essence and illustrate the pivotal role of the model in identifying and delineating caries in dental imagery.

- Conclusion and Future Perspectives: The findings derived from the model's performance were synthesized, leading to a comprehensive conclusion. Potential applications of the deep CNN model in dental caries detection were deliberated upon, accompanied by a reflection on the study's limitations. Additionally, areas warranting future research and development within this domain were proposed, aiming to advance the efficacy and scope of dental caries detection methodologies.

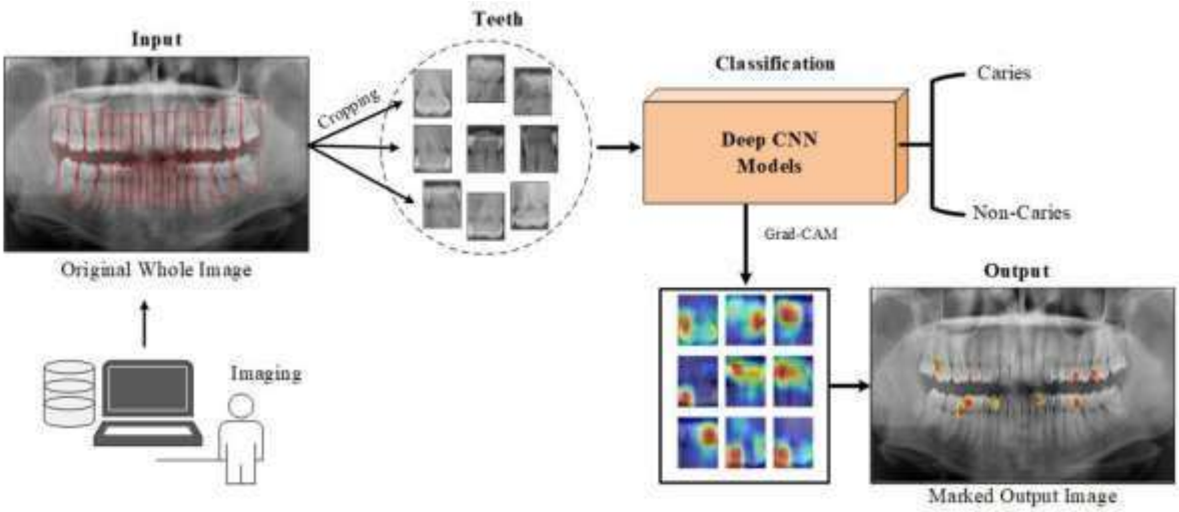

Fig. 6: Process of Dental Caries Detection.

System Architecture:

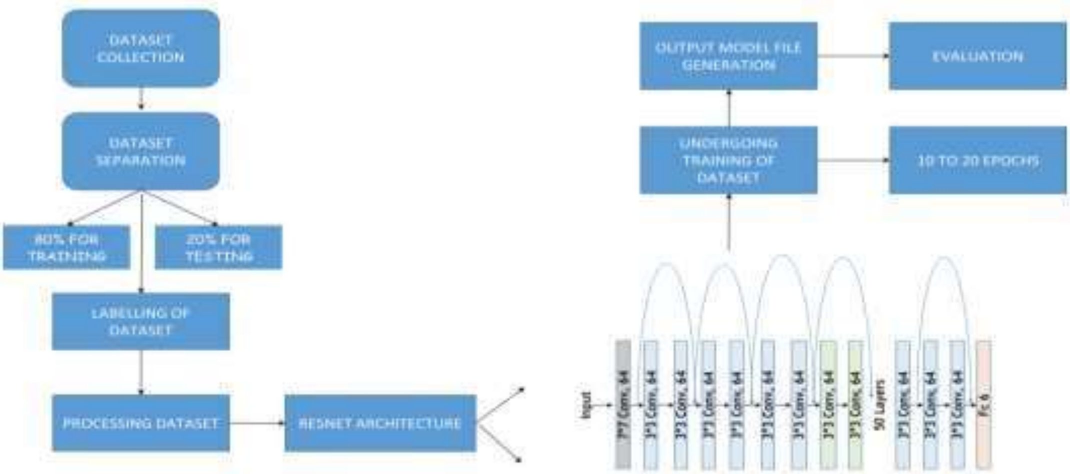

Fig. 7: System Architecture.

5.1 Dataset

The dataset of 2890 bitewing radiographs is divided into three subsets to train, validate, and test the deep learning models effectively. The training set comprises 90% of the data (2592 images) and is used to teach the model to identify patterns related to dental caries. The validation set, consisting of 6% of the data (177 images), is utilized to fine-tune hyperparameters and avoid overfitting. Finally, the test set, making up 4% of the data (121 images), is employed to evaluate the model's performance on unseen data, ensuring an unbiased assessment of its accuracy and generalizability.

5.2 Image Pre-Processing

Image preprocessing is a crucial step in the workflow of dental caries detection using deep learning. Effective preprocessing enhances the quality of input images, making it easier for convolutional neural networks (CNNs) to learn and detect features indicative of dental caries. This section outlines the preprocessing techniques applied to bitewing radiographs, including auto-orientation and resizing to a standard dimension of 640x640 pixels.

5.2.1 Auto-Orientation

Auto-orientation is the process of correcting the orientation of an image based on its metadata. Bitewing radiographs, like other medical images, may be captured or stored in different orientations due to various reasons such as the position of the X-ray machine or how the radiograph is handled. Auto-orientation ensures that all images are aligned consistently, which is essential for accurate analysis and feature extraction by deep learning models.

Procedure:

- Extract orientation metadata from the image file.

- Rotate the image to the correct orientation based on this metadata.
- This step eliminates the need for manual intervention, ensuring that all images are consistently oriented.

Benefits:

- Ensures uniformity in image presentation.
- Reduces the complexity of the dataset, allowing the model to focus on learning features relevant to dental caries detection.

5.2.2 Resizing

Resizing images to a fixed dimension is another critical pre-processing step. For this study, all bitewing radiographs are resized to 640x640 pixels. This standardization is necessary for several reasons:

Procedure:

- The original images, which can vary in size, are resized to 640x640 pixels using interpolation techniques.
- The resizing process involves stretching the image to fit the specified dimensions.

Benefits:

- Consistency: Provides a uniform input size for the neural network, which is essential for batch processing during training and inference.
- Computational Efficiency: Reduces the computational load by ensuring that all images are of the same size, optimizing memory usage and processing time.
- Model Compatibility: Ensures compatibility with pre-trained models and architectures that require specific input dimensions.

5.3 Image Augmentation

To enhance the training process and improve the generalization of our deep learning model, we applied several data augmentation techniques to the bitewing radiographs. For each training example, we generated three augmented versions using the following methods:

- Flip: We applied both horizontal and vertical flips to the images. This helps the model learn to recognize dental caries regardless of the orientation.
- 90° Rotation: Images were rotated 90 degrees clockwise and counter-clockwise to simulate different orientations.
- Crop: We performed random cropping with a minimum zoom of 0% and a maximum zoom of 27%, allowing the model to focus on different parts of the image and learn from varying scales.
- Rotation: Images were randomly rotated between -15° and +15° to simulate different angles at which radiographs might be taken.
- Shear: Images were sheared horizontally and vertically by up to ±10 degrees, simulating distortion and helping the model learn to recognize skewed features.
- Grayscale: We converted 15% of the images to grayscale, forcing the model to rely on texture and shape rather than color.
- Hue: The hue of the images was adjusted within a range of -15° and +15° to account for slight color variations.
- Saturation: The saturation of images was adjusted by a random factor between -25% and +25%, preventing the model from depending too heavily on color intensity.
- Brightness: The brightness of the images was adjusted by a random factor between -15% and +15%, helping the model handle varying lighting conditions.

- Exposure: We adjusted the exposure of images by varying the brightness between -10% and +10% to account for differences in lighting conditions.
- Blur: A random blur was applied to the images, with the blur radius up to 1 pixel to simulate minor blurring that can occur in real images.
- Noise: Up to 1.53% of the pixels in the images were altered with random noise to make the model robust to visual distortions.
- Bounding Box Adjustments: Bounding boxes were adjusted with a crop zoom range from 0% to 22% and exposure variation between -10% and +10% to keep annotations accurate after augmentations.

These augmentation techniques were chosen to create a more diverse training set, helping our model to better generalize to real-world variations in dental radiographs.

5.4 Feature Extraction and Image Classification

Datasets were sourced from Kaggle and Mendeley Data. These platforms provide comprehensive collections of labeled images necessary for training and evaluating our model. The datasets included various dental radiographs annotated with the presence or absence of dental caries, ensuring a diverse and representative sample for model training. For the model training process, we used a pre-trained transfer learning model named YOLOv8 and a Convolutional Neural Network (CNN) model for prediction with the architecture shown in Figure 9 and Figure below.

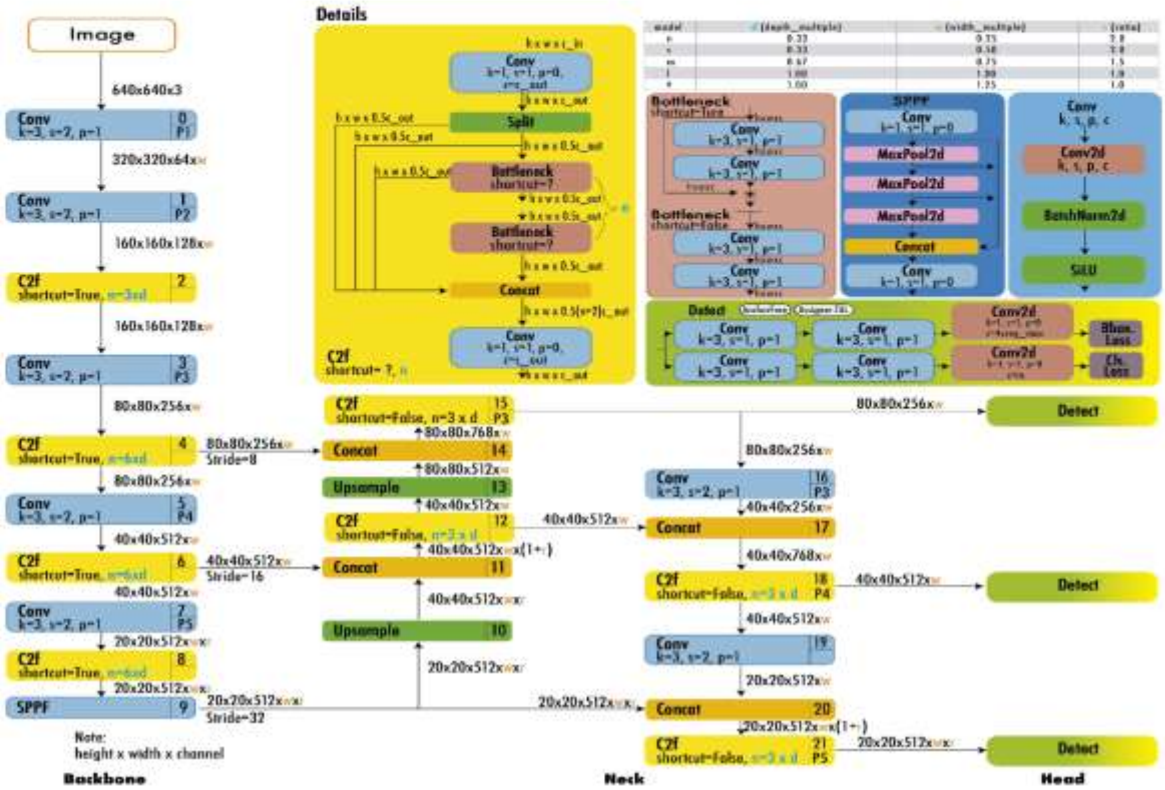

Fig. 8: YOLOv8 Architecture.

YOLOv8 was released in January 2023 by Ultralytics, the company that developed YOLOv5. YOLOv8 provided five scaled versions: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large) and YOLOv8x (extra-large). YOLOv8 supports multiple vision tasks such as object detection, segmentation, pose estimation, tracking, and classification.

Figure 8 shows the detailed architecture of YOLOv8. YOLOv8 uses a similar backbone as YOLOv5 with some changes on the CSPLayer, now called the C2f module. The C2f module (cross-stage partial bottleneck with two convolutions) combines high-level features with contextual information to improve detection accuracy.

YOLOv8 uses an anchor-free model with a decoupled head to process objectness, classification, and regression tasks independently. This design allows each branch to focus on its task and improves the model’s overall accuracy. In the output layer of YOLOv8, they used the sigmoid function as the activation function for the objectness score, representing the probability that the bounding box contains an object. It uses the SoftMax function for the class probabilities, representing the objects' probabilities belonging to each possible class.

YOLOv8 uses CIoU and DFL loss functions for bounding-box loss and binary cross-entropy for classification loss. These losses have improved object detection performance, mainly when dealing with smaller objects.

YOLOv8 also provides a semantic segmentation model called YOLOv8-Seg model. The backbone is a CSPDarknet53 feature extractor, followed by a C2f module instead of the traditional YOLO neck architecture. The C2f module is followed by two segmentation heads, which learn to predict the semantic segmentation masks for the input image. The model has similar detection heads to YOLOv8, consisting of five detection modules and a prediction layer. The YOLOv8-Seg model has achieved state-of-the-art results on various object detection and semantic segmentation benchmarks while maintaining high speed and efficiency.

YOLOv8 can be run from the command line interface (CLI), or it can also be installed as a PIP package. In addition, it comes with multiple integrations for labeling, training, and deploying.

Evaluated on the MS COCO dataset test-dev 2017, YOLOv8x achieved an AP of 53.9% with an image size of 640 pixels (compared to 50.7% of YOLOv5 on the same input size) with a speed of 280 FPS on an NVIDIA A100 and TensorRT.

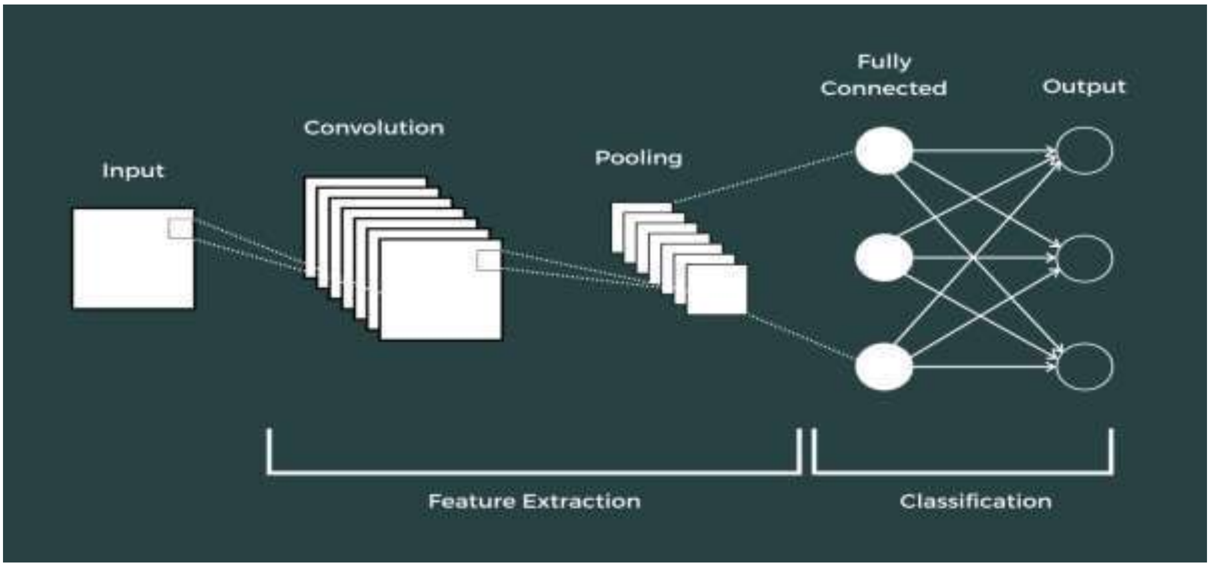

Fig. 9: CNN

Convolutional networks are composed of an input layer, an output layer, and one or more hid-den layers. A convolutional network is different than a regular neural network in that the neurons in its layers are arranged in three dimensions (width, height, and depth dimensions). This allows the CNN to transform an input volume in three dimensions to an output volume. The hidden layers are a combination of convolution layers, pooling layers, normalization layers, and fully connected layers. CNNs use multiple convolutional layers to filter input volumes to greater levels of abstraction.

CNNs improve their detection capability for unusually placed objects by using pooling layers for limited translation and rotation invariance. Pooling also allows for the usage of more convolutional layers by reducing memory consumption. Normalization layers are used to normalize over local input regions by moving all inputs in a layer towards a mean of zero and variance of one. Other regularization techniques such as batch normalization, where we normalize across the activations for the entire batch, or dropout, where we ignore randomly chosen neurons during the training process, can also be used. Fully-connected layers have neurons that are functionally similar to convolutional layers (compute dot products) but are different in that they are connected to all activations in the previous layer.

5.5 Convolutional Neural Network (CNN)

In the final stage of dental disease recognition, a convolutional neural network (CNN) is employed. Before feeding the images into the CNN, they are stretched to a size of 640x640 pixels. This resizing process is necessary to standardize the input dimensions for the neural network. By stretching the images to a uniform size, we ensure consistency in the input data format across all samples. This is crucial for neural networks, as they require fixed-size input tensors to operate efficiently. Moreover, resizing the images to a larger dimension like 640x640 helps preserve finer details and features in the images, which can be crucial for accurate disease recognition.

ResNet is utilized in the feature extraction phase of the process. ResNet, with its deep architecture and residual connections, excels at capturing complex hierarchical features from images. In this context, ResNet serves as a feature extractor, where it processes the input images and extracts high-level features relevant to dental disease recognition. By leveraging pre-trained ResNet models, we can benefit from the knowledge learned from vast datasets (such as ImageNet) and transfer it to our specific domain, reducing the need for extensive training data and computation resources.

After feature extraction with ResNet, the output of the transfer learning model, which consists of the extracted features, is fed into the CNN model according to the network of Russakovsky. This likely refers to a specific architecture or configuration proposed by Russakovsky et al. for image classification tasks. The CNN model, likely customized for dental disease recognition, further processes the extracted features to make predictions regarding the presence or absence of dental diseases in the input images. This two-stage approach allows for a more efficient and effective utilization of deep learning techniques, leveraging both the strengths of pre-trained models and domain-specific CNN architectures for accurate disease recognition.

For detailed object detection tasks, we used the YOLOv8 (You Only Look Once version 8) architecture, specifically designed for real-time object detection. YOLO's ability to detect multiple objects in an image quickly and accurately makes it ideal for identifying dental caries in radiographs.

CHAPTER 6

RESULTS

In this study, a deep learning model was developed for dental caries detection. The confusion matrix shown in Figure 10, demonstrates the classifier's performance in distinguishing between dental caries and no caries cases, achieving an accuracy of approximately 90.1%. For dental caries, the model has a precision of 97.3%, a recall of 85.7%, and an F1-score of 91.1%. For no caries, the model's precision is 82.4%, recall is 96.6%, and F1-score is 88.9%. These metrics indicate that the classifier performs effectively, with a strong balance between precision and recall in identifying both conditions.

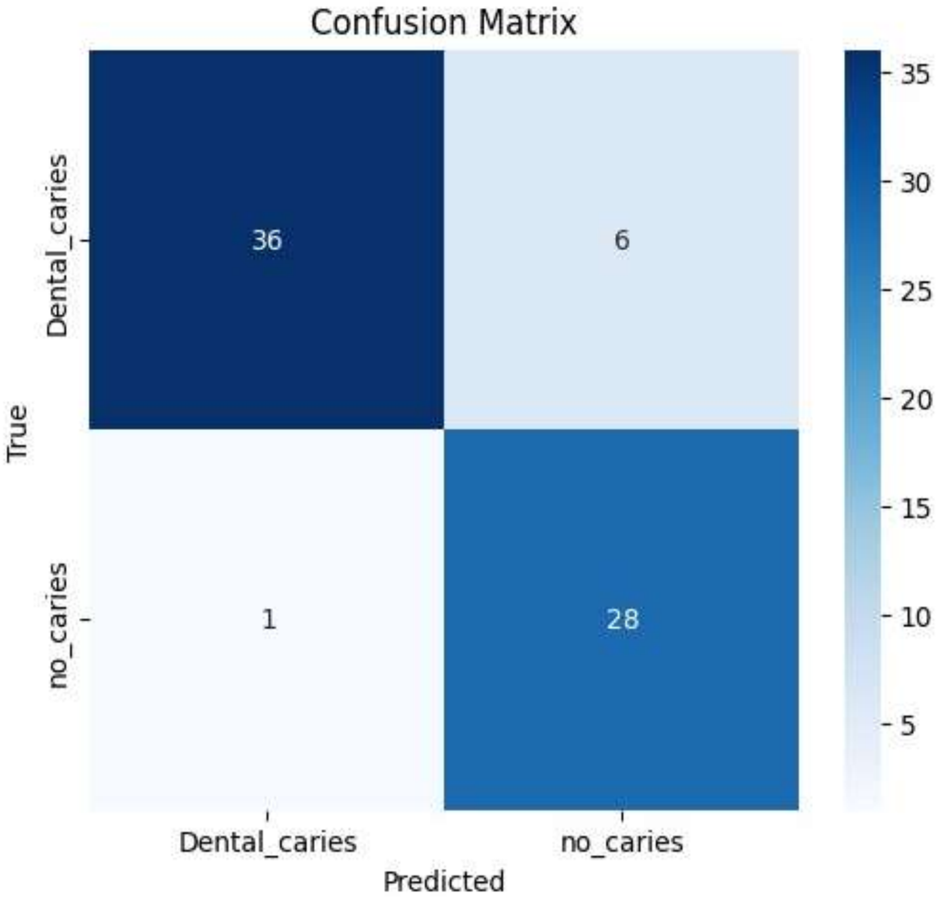

Figure 10: Confusion Matrix.

```
Accuracy: 0.9014084507042254
Precision: [0.97297297 0.82352941]
Recall: [0.85714286 0.96551724]
F1-score: [0.91139241 0.88888889]
```

Fig. 11 Classification Report.

These results underscore the model's reliability and effectiveness in identifying dental caries, highlighting its potential as a valuable tool for dental diagnostics. This performance suggests that the model is well-suited for practical applications in clinical settings, particularly in the accurate detection of dental caries.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusion

In this project, we applied deep learning algorithms, specifically ResNet architecture coupled with CNN, to detect dental caries. Our experiments demonstrated the effectiveness of this approach in accurately identifying dental cavities, reducing the need for multiple doctor consultations. ResNet's deep architecture enabled the extraction of intricate features from dental radiographs, while CNN efficiently categorized these features to make precise predictions. This combination improved dental cavity detection efficiency and reliability, minimizing human intervention. Our work represents a significant advancement in dental healthcare, introducing an automated, cost-effective diagnostic method. Future research in this area could revolutionize dental care by offering timely, accurate oral health assessments and reducing reliance on manual examinations.

7.2 Future Work

There are issues and encouraging future perspectives of study which have popped out from our discussions here and they are highlighted as follows:

- Data availability and reliability: Deep learning networks require large amount of data to be able to achieve meaningful and effective performance results. Due to the nature of dental images, there is a need for hybrid datasets to aid good performance of the networks. There is a need for publicly available datasets for dental images to make deep learning in the field possible.
- Large-Scale Dataset Construction: Construction of larger and more diverse datasets of annotated dental images is essential for training deep learning models with improved generalization and robustness.

Collaborative efforts among dental practitioners, researchers, and institutions to collect and annotate high-quality data can contribute to the development of more effective detection systems.

- Fine-Grained Localization and Segmentation: Developing deep learning models capable of not only detecting dental caries but also accurately localizing and segmenting the affected areas within the teeth can provide valuable insights for treatment planning and intervention. Research in semantic segmentation and instance segmentation techniques tailored to dental images could facilitate precise lesion delineation.
- Hybrid approaches: Deep neural networks can also be achieved by combining several models or methods to form hybrid networks that will improve overall evaluation performance. The combination can be in any stage of the model, for instance, combining two preprocessing techniques to come with a single one to enhance image quality. This combination can also be handled by joining various attributes of different models to form one hybrid model that will enhance training, extraction, detection, and classification of objects. Combination of different convolution networks to form one hybrid network will be a good area to explore. This will save the long training and testing times that come with large networks having many convolution networks.
- Explainable AI and Interpretability: Investigating methods for enhancing the explainability and interpretability of deep learning models for dental caries detection is vital for gaining the trust of clinicians and patients. Techniques such as attention mechanisms, saliency maps, and feature visualization can provide insights into the decision-making process of the models and aid in understanding the underlying factors contributing to the predictions.
- Continual Learning and Adaptation: Developing deep learning models capable of continual learning and adaptation to evolving dental conditions and patient demographics is essential for maintaining optimal

performance over time. Research in incremental learning techniques and adaptive model architectures can enable the continuous improvement and refinement of detection systems in response to new data and clinical insights.

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