Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, No.3, April : 2025

A REVIEW OF DEEP LEARNING APPLICATIONS IN DENTAL DISEASE IDENTIFICATION AND CLASSIFICATION

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Abstract—The dental field is increasingly integrating deep learning techniques, as Dental conditions continue to be a major health risk.The use of deep learning techniques in the diagnosis of a range of dental disorders, such as tooth recognition, dental decay, rehabilitative teeth, implants for teeth, and endodontic treatments, is examined in this review in the literature, through image analysis. Numerous classification and segmentation algorithms have been developed to extract critical features from dental radiographs, enhancing diagnostic accuracy. Convolutional Neural Networks (CNNs) are important for predicting affected teeth, where models are trained, validated, and tested based on labeled dental image datasets. Additionally, deep learning hybrid models and sophisticated segmentation architectures have been investigated to enhance diagnostic efficiency and accuracy. Deep learning's capability in revolutionizing dental imaging through less dependence on human interpretation and enhancing clinical decision-making is presented in this review.
***Keywords*: Dental diseases, Dental radiographs, Deep Learning, CNN, Image segmentation, Hybrid models**

I. INTRODUCTION

The human buccal cavity is distinguished by the predominance of dental caries, caused largely by infections produced by bacteria[1]. It is vital to diagnose early the prime reason for cavities because treatment will be less challenging and the disease is prevented in comparison to progress[2]. Radiological tests like dental X-rays are usually utilized by dentists in identifying patients' oral conditions [3]. Dental imaging analysis has changed with the advent of deep learning techniques into a central element in the enhancement of diagnostic processes and the speedup of clinical decision-making[4]. By examining and extracting meaningful features from dental radiographs, these methods facilitate the identification of numerous dental conditions[5], such as tooth verification, cavities, fixed teeth, implant dentistry, and endodontic treatments[6]. The use of deep learning will be capable of reducing the diagnosis time significantly and improving the detection rate of the underlying dental issues[7], which allows for faster and improved treatments[8].

Figure 1.PanoramicImage

Radiographs are the most crucial tools utilized in surveillance, evaluation, and diagnosis of conditions and diseases of the mouth[9]. Panoramic radiography of the teeth is a most common form of radiograph in dental examinations for general assessment. In addition to panoramic X-rays, there are other imaging techniques that researchers aim to make accessible to enhance the diagnosis of conditions of the mouth [10]. Image segmentation is the fundamental process for the detection of early dental issues, setting the stage for accurate disease diagnosis. Boundary, cluster, region, and watershed segmentation are some of the common techniques in medical images[11]. Among these, semantic segmentation is highly critical in detecting and labeling tooth contours and jaw contours correctly, which is fundamental in effective dental diagnosis[12].

A. Input Modalities:

Intraoral or extraoral radiographs are the two primary categories of dental radiographs. Intraoral radiographs provide accurate information regarding dental arrangement, root canal infection, and caries detection[13]. This category entails a variety of categories, some of which are peripical images[14], which capture the roots and bone structures of 2-3 teeth, bitewing images, which are used to calculate the upper and lower teeth's alignment, a prerequisite for treatments like restoration of teeth or capping[15], and occlusal images, which capture the bottom of the mouth and reveal details about the jaw's bite. Extraoral radiographs, on the other hand, capture images of the entire skull and jaws, offering broader diagnostic information. These include Panoramic X-rays[16], and these are often used for identifying fractures, trauma, mandible ailments, or pathological lesions[17]. The mandible, dentition, and related tissues are uncovered by cephalometric X-rays, which provide a side-view of the head. Sialograms, which take radiographs of salivary ducts as well as glands, Cone-beam computed tomography (CBCT) produces defined three-dimensional images of dental usage, nerves, soft tissues, and bones, while computed tomography (CT) gives 3D views of internal components .

Panoramic radiographs are commonly used in dental examinations because they give a good overview of the maxillary and mandibular areas, and hence a thorough evaluation can be made. The 3D structures are then mapped onto 2D images, which is ideal for further examination.

Deep learning's incorporation for dental image processing could potentially transform diagnostic processes, streamlining them into faster, more accurate and less interpretive manual processes. AI-based technology' incorporation into dental imaging may eventually contribute to improved patient care through precise, real-time information on oral health status.

B. Deep Learning Approaches in Dental Image Analysis and CNN

Deep learning has emerged as a swiftly growing research topic in medical image processing, with significant potential for disease diagnosis by identifying their existence and absence. The ability of deep learning models to learn automatically is a characteristic feature, making them extremely effective for structured data as well as unstructured sources. The capability of C.N.N. in solving complex issues like segmenting pictures, classification, and object detection, has been specially noted due to advances in deep learning. CNNs are regularly used in image analysis because they can process very large amounts of data and automate the recognition and classification of images tasks.

CNNs are suitable for image classification because of their capability to recognize visual patterns over raw pixel information with limited preprocessing. Classification of an image into specified classes is accomplished via methods for classifying and extracting features. C.N.N.s use convolutional filters in order to extract features, while fully connected layers are used for outputting final prediction of classifications

While CNNs offer exceptional accuracy in image processing and feature detection, they do require large, labeled datasets and can be computationally intensive, leading to slower operation times.

Object detection in medical diagnosis is a major role to undertake while detecting particular regions of interest from an image. It is assumed to detect tiny regions of importance within a common image to aid specialists in providing faster and more accurate diagnoses. Object detection tools like region-based detectors and classifiers try to computerize the detection of major features. The Region-based CNN model was developed to solve this issue, and it has undergone various stages: from R-CNN to Fast R-CNN , Faster R-CNN , Mask R-CNN , and very recently G-R-C.N.N. These models involve various steps such as classification, localization, region proposals, and deep CNN feature extraction to enhance detection accuracy. Concurrently, R-CNN models face challenges, such as redundant areas and lengthy multi-step training procedures. Edge Box method and hierarchical segmentation have been suggested as solutions to enhance efficiency.

Fast R-CNN, a subsequent development, offers enhanced performance and efficiency, especially in tasks involving classifications and bounding box regression. Mask R-CNN (MRCNN) takes this to the next level by incorporating the image and instance segmentation functionality, allowing the model to not just classify objects but to also predict segmentation masks for regions of interest. More recent advancements in object detection include frameworks like YOLO (You Only Look Once), which is known for its real-time object detection capabilities, and other models like RetinaNet, SSD, and YOLOR, each offering improvements in speed, accuracy, and robustness[38]. YOLO has evolved through multiple versions (YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, and YOLOv7), with implementations in deep learning libraries such as Keras and OpenCV.
Feature extraction is used in the field of picture classification to identify trends in the data. This is often accomplished by using traditional CNN designs like as LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, while DenseNet.. InceptionV3, ResNet50, and Xception are recent models that have been found to achieve minimal validation losses in just a few epochs (3–4 epochs) and obtain validation accuracy rates as high as 99% in recent studies on loss values and accuracy during both the training and validation phases. DenseNet-121 and ResNet-50 have demonstrated the highest training accuracy, with DenseNet-121 demonstrating the lowest loss during training. On the other hand, Inception-ResNet-V2 and VGG16 models achieve superior validation accuracy.
In the context of semantic segmentation, which involves identifying and labeling distinct regions in an image, CNNs and Transformers are the two main architectures used. U-Net, a robust architecture that was initially developed for biomedical image analysis, has been extensively employed to segment images from a variety of modalities, such as X-rays, CT scans, MRIs, and ultrasounds. U-Net variants, including 3D U-Net, attention U-Net, and inception U-Net, have been created to enhance the network's efficacy by modifying feature extraction methods or filtering with multiple scales. Further improvements have led to the creation of UNet++, and UNet 3+, which focus on reducing network parameters while improving computational efficiency[44]. Networks like VNet, FCN, and 3D U-Net+ResNet also contribute to the segmentation of both 2D and 3D images, enhancing the segmentation capabilities for medical applications.

II. Related work:

J. W. Lim (2024): Lim et.al presented a method to detect periapical lesions from periapical radiographs using the ConvNeXt model. The network was trained using 2,500 periapical X-rays & had a 97.5% accuracy gg [21]. **S. S. R. K. Sumanet (2024)**: This research provides a unique approach for classifying dental diseases using dental X-ray pictures and C.N.N.s[22]**C. Kim(202o)**: Kim et al. proposed a C.N.N.-based method for the automatic panoramic dental identification system radiographs. Their suggested model, which was trained on 4,200 panoramic radiographs dataset, had the ability to classify and detect tooth numbers with an accuracy of 96.7%[23]. **A. Singh (2020)**: Singh and his team explored the use of deep learning in the recognition of dental radiographs. In their research, they used several deep learning architectures, such as CNNs, on a set of 5,000 dental X-ray images[24]. **J. Lee (2022)**: A Lee and colleagues proposed a technique for automatically detecting and classifying teeth on panoramic radiography. The accuracy of the model, which was developed on 4,500 panoramic X-ray pictures, was 94%.[25].**Lawrence Y.(2020)**Lawrence et al. have come up with a method for dental X-ray classification based on an 18-layer convolutional neural network (CNN)[26].
Muthu Lakshmi (2020) Muthu Lakshmi and her colleagues utilized a Deep CNN algorithm based on the AlexNet model to forecast dental problems. The research used 1,700 dental images, divided into 900 for training and 800 for testing[20]. **MajedBouchahmaet(2019)** An automated method for identifying dental issues such as fillings, root canals, and fluoride treatments from dental X-ray images was proposed by Bouchahma[27].**Lizheng Liu (2020):**Liu created a intelligent dental diagnostic system based on the MASK R-CNN model. Their research trained a model on 600 clinical dental images to diagnose dental disease automatically[19].

Yusuf Bayraktaret.(2022) Bayraktar and Ayan utilized the YOLO v3 model to identify dental caries through the use of bitewing radiographs. In their investigation, they aimed to identify caries on premolars and molars[28].

Joni Hyttinenet (2020) Hyttinen and others investigated the improvement in dental images through the use of spectral images to diagnose conditions like gingival recession, gingivitis, caries, and leukoplakia[29]. **DeveshSaini (2021)** Saini et al. suggested a Deep CNN model to identify dental caries from a dataset of 500 colored dental images. The data set was split into training data consisting of 400 images, 70 for validation, and 30 for testing[30].**Umer Rashid (2022)** Rashid et al. presented a hybrid approach with ResNet50 as the pre-trained network and Mask R-CNN for identifying dental pathologies. On a training set of 508 periapical radiographs and a test set of 100, the model had an accuracy of 78%[31].

Table 1. Performance of Deep Learning Methods in Dental and Oral Diagnostics

Method	Images Type	Disease	Accuracy
Enhanced ResNet50 with SimAM	Dental Images	Dental Diagnostics	0.676
FUSegNet with Attention Gates	Panoramic X-rays	Teeth Segmentation and Orientation	IoU: 82.43%, DSC: 90.37%
M-Net with Swin Transformers and Teeth Attention Block (TAB)	Panoramic X-rays	Multiclass Teeth Segmentation	Outperformed existing state-of-the-art methods
Hybrid Mask R-CNN	Periapical	Dental Caries	78%, Correctness: 92%
CNN-PCA-KNN	Panoramic	Age estimation using OPG	99.98%
Multi-Input Deep CNN	Periapical	Dental Caries	99.13%
CNN	Colour images	Oral Cancer and Dental Caries	83–94%
CNN YOLO v3	Bitewing	Caries, lesions	94.59%
Deep CNN	Digital colour image	Dental Caries	Inception-V3: 99.89%, ResNet50: Loss: 0.01%
PCA	Spectral Images	Oral lesions	-
CNN	Periapical	Normal teeth, implants, fillings, teeth cavity	93.04%
CNN	Panoramic	Maxillofacial segmentation	99.28%

3. Imaging Modalities for Dental Disease Diagnosis

Dental Radiography in Diagnosis

Dental radiography (X-ray) continues to be the most frequently employed imaging modality by dentists for the diagnosis of dental issues, such as lesions ;periapical pathosis, and dental restorations. It is also crucial for the evaluation of overall oral health; Cantu et.al, 2020; Chang et.al, 2020; Lee et.al, 2021). In Figure 2, examples of imaging modalities that are employed in research to diagnose dental diseases are illustrated. The subsequent subsections address these modalities and their distinctive attributes.

3.1 X-ray Imaging Systems

Digital X-ray imaging has largely replaced traditional photographic X-ray films, relying on advanced sensing to generate better oral anatomy photos. Traditionally, dentists analyze these images to detect problems like cavities as well as tooth lesions and develop treatment plans. Various types of X-rays are used to capture different perspectives of the mouth. For instance:

1. **Intraoral Radiographs**: Primarily used for detecting dental cavities and monitoring oral health.
2. **Extraoral Radiographs**: Utilized to diagnose potential issues with the mandible, facial bones, or teeth, evaluate jaw growth and development, and identify impacted teeth.

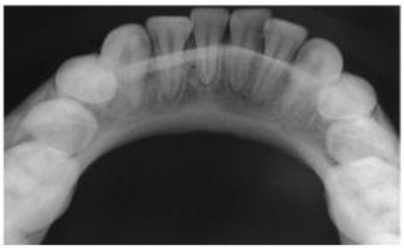

Figure 2. Intraoral X-ray Imaging

Figure 3.Fluorescence Hyperspectral Imaging

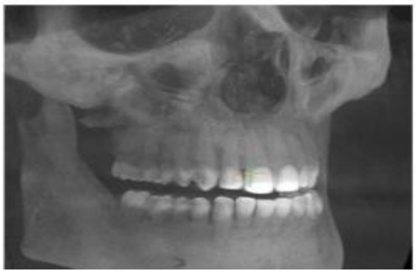

Figure 4. Extraoral X ray imagning

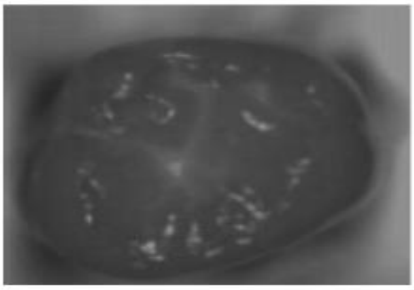

Figure 5. Spatial Frequency Domain Imaging

3.1.1 Intraoral X-ray Imaging

Intraoral radiographs are among the most frequently utilized imaging methods in dentistry[82], offering high spatial resolution that is critical for identifying dental and jawbone diseases. These images also provide insights into bone structure and density. Two techniques are commonly used for obtaining intraoral radiographs: strategies for bisecting as well as matching angles.

The paralleling technique involves the application of radiation to the sensor, which has its position parallel to the tooth's plane[25]. In contrast, the bisecting angle technique positions the receptor in close proximity to the tooth, making certain that the centre X-ray beam gets perpendicular of the imaginary line who divides the angle formed by the receptor plane and the tooth's long axis. The primary intraoral radiograph types that are frequently used as dental diagnosis and treatment planning are listed below:

- **Bitewing X-ray**: provides a thorough overview of the mandibular as well as maxillary arches in a particular area, helping detect tooth decay, restorations, and variations in dental decay.
- **Periapical X-ray**: Captures a complete view of individual teeth, including their roots and surrounding bone structures, aiding in identifying root abnormalities and specific dental issues.
- **Occlusal X-ray**: Displays the positioning and developmental stages of teeth in the maxilla or mandible.

3.1.2 Extraoral X-ray Imaging

Extraoral imaging is frequently employed to investigate the connections between the temporomandibular joint (TMJ), mandible, and teeth[83]. Its primary objective is to diagnose problems in the jaw and cranium regions. The following are common extraoral imaging methods:

- **Panoramic X-ray**: Offers a two-dimensional perspective of the entire buccal cavity, which encompasses the mandible and maxilla.It is particularly useful for identifying Dental tumour diagnosis and teeth that impacted.
- **Lateral Cephalogram**: Offers a profile view of the head, aiding in analyzing jaw alignment and creating therapy programs.
- **Cone-Beam Computed Tomography (CBCT)**: Overcomes the limitations of traditional radiography by providing detailed three-dimensional images of internal structures. This imaging technique is especially useful for identifying fractures and tumors and supports surgical planning to avoid complications.

3.2 Near-Infrared Imaging Systems

Dental caries is detected using a non-ionizing optical technology known as near-infrared (NIR) imaging. It uses long-wavelength radiation to penetrate tooth structures, producing high-contrast images that differentiate between healthy and carious tissues. This method minimizes radiation exposure while enhancing image quality[86].

- **Fluorescence Hyperspectral Imaging**: This non-contact diagnostic method captures both spatial and spectral information, enabling precise optical characterization of dental issues, such as plaque and caries. It uses line-scanning cameras with high spectral resolution to generate data suitable for computer vision processing.
- **Spatial Frequency Domain Imaging (SFDI)**: A quantitative imaging technique that separates scattered and absorbed light components by projecting modulated fringe patterns at varying depths and frequencies[87].

3.3 Spectral Ranges in Dental Imaging

Various spectral bands are explored in dental imaging to detect and analyze lesions based on the chemical composition of dental tissues[88]:

- **Near-, Mid-, and Long-Infrared**: These ranges provide information on tissue molecular structures, aiding in lesion detection. Infrared is categorized into near (4000–14,000 cm^{-1}), mid (400–4000 cm^{-1}), and far-infrared (25–400 cm^{-1}).
- **Ultraviolet (UV)**: Wavelengths between 100 and 400 nm are used for detecting caries and assessing dental materials through fluorescence techniques.
- **Radio Frequency (RF)**: MRI, which uses non-ionizing RF pulses within a controlled magnetic field, helps in dental implant planning by providing detailed information about bone density and contours[89].

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, No.3, April : 2025

3.4 Challenges in Automated Dental Disease Diagnosis

Artificial intelligence (AI) models are increasingly applied to predict and diagnose dental diseases, but several challenges remain:

- **Limited Data**: Privacy concerns and the lack of structured, comprehensive datasets restrict the application of AI in dental imaging.
- **Data Annotation**: Labeling medical data is costly and requires domain expertise, which limits the availability of annotated datasets for training AI models.
- **Generalizability**: Variations in imaging characteristics across datasets hinder the generalizability of AI models.
- **Class Imbalance**: The prevalence of normal samples compared to abnormal ones biases AI algorithms toward majority classes.
- **External Validation**: Inconsistent validation practices affect model reproducibility and transparency. Establishing standards for benchmarking and sharing is crucial.

4. DATASETS

Because deep learning models have access to large datasets like ImageNet, PASCAL VOC 2007/VOC2012, Microsoft COCO, as OpenImages, they have shown promise in object recognition[90]. Additional datasets such as Caltech10/101, NORB (50 toy images), MNIST (handwritten digits), and LabelMe (web-based annotation tool and dataset) have further expanded the field.In dental imaging, labeledmedical pictures or publicly available data are the preferred sources for training models, providing domain-specific data for precise diagnostics. Below is a list of publicly available dental datasets.

Table 2: PubliclyAvailable Dental Image Datasets

Dataset	Image Type	Number of Images	Description
LMCD-OR	Oral radiographs	3,818	An extensive multilevel categorised oral radiography diagnostic dataset, designed to support AI-driven diagnostics. It includes detailed annotations for various oral health conditions.
Multi-center Dental Panoramic Radiography Image Dataset	Panoramic radiographs	6,536	A dataset encompassing images from multiple centers, labeledhelping with segmentation and classification duties of dental caries, periodontitis, and impacted teeth.
OdontoAI	Panoramic radiographs	4,000	A human-in-the-loop labeled dataset aimed at expanding the study of panoramic radiographs for teeth, with 2,000 images publicly available for model training.
Teeth3DS	Intra-oral 3D scans	1,800	A reference dataset for labelling and segmenting teeth from intraoral 3D images, 900 patients' worth of data, covering the upper as well as lower jaws independently.
CTooth	Cone Beam Computed Tomography (CBCT) images	7,363 slices	CBCT picture tooth volume segmentation benchmark and fully highlighted 3D dataset with fine-grained tooth labels annotated by qualified radiography interpreters.

CTooth+	Dental CBCT images	168 volumes	An extension of the CTooth dataset, offering a large-scale dental CBCT dataset and standard for segmenting tooth volume , including both labeled and unlabeled volumes.
Tufts Dental Database (TDD)	Panoramic radiographs	1,000	A multimodal panoramic X-ray dataset labeled with maxillomandibular regions, anomalies, and teeth, designed for benchmarking diagnostic systems.
Oral and Dental Spectral Image Database (ODSIDB)	Spectral images of oral and dental structures	316	A dataset comprising spectral images aimed at enhancing visualization and analysis of oral lesions and dental conditions.
Periapical Radiograph Dataset	Periapical radiographs (top to bottom jaw)	120	A collection of periapical X-ray images intended for caries screening and other dental assessments.
Panoramic Dental X-ray Dataset	Panoramic radiographs	1,500	A dataset featuring panoramic X-ray images, useful for tasks like teeth segmentation and dental anomaly detection.
Anonymized Panoramic Radiograph Dataset	Anonymized and de-identified panoramic radiographs	116	A set of panoramic X-ray images with anonymized patient information, facilitating research in automated dental analysis.

4.1 Overview of Dental X-ray Datasets

Panoramic Dental X-ray Dataset: 2,000 images from 116 patients using SoredexCranex D. Includes healthy teeth, partially/completely edentulous cases. Organized by qualitative features.
Applications: Studying dental conditions and structural features.
UFBA-UESC Dental Image Dataset: 1,500 images categorized by dental restorations, appliances, implants, and extra teeth. Captured using ORTHOPHOS XG 5 X-ray camera.
Applications: Semantic segmentation and classification research
Tufts Multimodal Dataset: 1,000 labeled images with segmentation masks, eye-tracking maps, and region-of-interest masks. Annotated for abnormalities like periapical and odontogenic issues.
Applications: Development of advanced segmentation and diagnostic tools.

4.2. Evaluation Metrics

The efficacy of algorithms utilized in dental diagnosis is assessed using a variety of metrics. This section highlights the commonly used metrics and their foundational concepts:

- **True Positive (TP):**Situations in which the algorithm or the ground truth both indicate a favorable outcome.
- **True Negative (TN):** Situations in which the algorithm or the ground truth both indicate a negative result.
- **False Positive (FP):** Situations in which the algorithm anticipates a positive result, but the ground reality suggests a negative one.
- **False Negative (FN):** Situations in which the algorithm anticipates a negative result, but the ground reality suggests a positive one.

Key performance metrics include:

- **Accuracy:**The proportion of all forecast that are realistic (positive and negative) out of the total samples.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 4, No.3, April : 2025

- **Precision:**The percentage of favourable results that was correctly forecasted to the total number of predicted positives
- **Specificity:**The percentage of actual negative forecasts among all negative selections.
- **Sensitivity (Recall):**The percentage of accurately detected positives among all real positive samples is known as the true positive rate.

5. Approaches to Dental Disease Diagnosis Using X-ray Imaging

This section emphasizes a variety of research endeavors that are designed to diagnose dental diseases with X-ray imaging. Figure 3 illustrates the typical stages of the dental disease diagnosis process, from data acquisition for diagnosis. An overview of research, arranged according to the application of artificial intelligence, the methods utilized, and the specific dental issues addressed, is provided in Table 3

Table 4. Applications of Techniques in Dental Image Analysis and Diagnostics

Application	Technique	Target Problem and Study Number
Image Enhancement	Classical Image Analysis	Adjusting the contrast and reducing the image
	ML	Visibility enhancement
	Deep Learning	Noise reduction, resolution enhancement
Disease Detection	ML	Vertical root fracture, dental anomaly identification
	Deep Learning	Periodontal loss of bones, dental tumours, periapical pathosis, tooth counting, and tooth detection and recognition
Disease Classification	Classical Image Analysis	Dental disease, osteoporosis evaluation, and dental detection
	ML	Dental caries, pre-molar and molar teeth, periapical lesions, dental repairs, periapical roots, teeth and roots, sagittal patterns, proximal dental caries, and osteoporosis
	Deep Learning	Dental deterioration, both periodontitis, tooth designation, dental implant phases, dental fixture categorisation, bone loss, and approximate dental caries.
Disease Segmentation	Classical Image Analysis	Delineation of dental cysts, tooth deterioration, tooth edge reinforcement, and feature extraction
	ML	Assessment of maxillary structural variation, dental disease, bone loss, the tooth decay
	Deep Learning	Finding molars and premolars, identifying broken and deteriorated human remains, identifying early lesions, determining the alveolar bone level, and locating teeth

5.1. Image Enhancement

The resolution of radiographic images has been enhanced through the use of a variety of image enhancement techniques. Lin et al. employed a combination of adaptive contrast stretching and homomorphic filtering to improve X-ray images, whereas Ahmed et al. concentrated on the contrast-limited adaptive histogram equalization (CLAHE), thereby improving diagnosability.Suprijantoet.al improved CLAHE by incorporating Rayleigh distribution, which yielded better image quality. Techniques like contrast stretching and Gaussian filtering have also been applied to enhance dental radiographs accuracy. In the realm of machine learning, Yousefiet.al proposed a wavelet image fusion technique combined with a Bayesian classifier to enhance dental X-rays.

5.2. Disease Detection

Machine learning algorithms, particularly deep learning methods, have been widely applied for disease detection using radiographs. Neural networks have shown their ability to detect vertical root fractures, especially with CBCT images, which provide more accurate diagnostic outcomes than conventional radiographs. Studies have also demonstrated that deep C.N.N. (DCNNs) can be used to detect periapical pathosis, tumors, and tooth anomalies with high accuracy. For instance, Miki et.al achieved a 91.0% accuracy in detecting dental pathologies with DCNNs. However, certain conditions, such as dental tumors, may require a biopsy for definitive diagnosis, and AI can serve to alert clinicians rather than provide a final diagnosis.

5.3. Disease Classification

Support vector machines (SVM), fuzzy attribute-based methods, and K-nearest neighbors (KNN) are among the machine learning techniques that have been implemented to classify dental diseases. These methodologies are particularly successful in the examination of periapical lesions, osteoporosis, dental infections, and dental cysts. This gray-level co-occurrence matrix (GLCM) has been employed to classify dental maladies, in addition to texture feature extraction.A artificial multilayer perceptron artificial neural network was employed to detect proximal dental lesions in a notable approach, which resulted in a 39.4% improvement. However, challenges remain in classifying complex diseases like dental tumors, where automated systems can assist but not replace expert clinicians.

5.4. Disease Segmentation

Classical image analysis methods have been used to segment dental diseases, particularly for tooth and decay detection. Methods like directional bank filtering with the degree set approach(DDFBT) have been applied for segmentation in enhanced images. The Otsu method, widely used for thresholding, helps identify tooth decay by analyzing image enhancements to create larger threshold values for disease detection. Fuzzy clustering algorithms have also been proposed for improving disease pattern recognition in dental images. These segmentation methods are particularly valuable for identifying abnormalities in teeth and detecting diseases such as decay or periodontal issues, with various methods enhancing the segmentation process.

Table 5: Recent Advances in Dental Imaging and Landmark Detection

Methodology	**Task**	**Training Set**	**Test Set**	**Loss Function**	**Optimizer**	**Learning Rate**
UNet with three backbones	Tooth segmentation	85–150	Not specified	Cross entropy	Adam	0.0001
Multi-objective model	Abnormality detection and localization	900	100	Affine transformation, Binary cross entropy	Adam	0.0001
Hybrid UNet+Transformer approach	Tooth segmentation	1,200	300	Dice Similarity Coefficient (DSC), Cross entropy	Adam	0.0001
Three-stage cascaded CNN	Landmark detection	150	100	Affine Transformation	Adam	0.001

Table 6: Evaluation of Experimental Protocols on the UFBA-UESC Dental Image Dataset

Methodology	Task	Training Set	Validation Set	Test Set	Loss Function	Optimizer	Learning Rate
Two Feature Aggregation Module	Tooth Segmentation	1,200	150	150	Affine Transformation	Not specified	Not specified
Multiscale Structural Similarity	Tooth Segmentation and Root Boundary Extraction	1,200	150	150	Custom Hybrid Loss	Adam	0.0001
Two-Stage Attention Segmentation Network	Tooth Segmentation	1,200	150	150	Custom Hybrid Loss	Adam	0.001
BB-UNet (U-Net integrated with YOLOv8)	Instance Segmentation and Teeth Classification	425	Not specified	Not specified	Dice Coefficient	Not specified	Not specified

Table 7: Comparison of Performance Metrics for Cephalometric Landmark Detection

Methodology	2 mm	2.5 mm	3 mm	4 mm
Three-stage cascaded CNN	81.3%	89.9%	93.7%	97.8%
C.N.N. with pre-trained ResNet50	86.4%	91.7%	94.8%	97.8%
Bayesian C.N.N. (BCNN)	82.1%	88.6%	92.2%	95.9%

Table 8: Comparison of Tooth Segmentation (TS) Models

Task	Accuracy (%)	Specificity (%)	Precision (%)	F1 Score (%)	Recall (%)	Dice Score (%)
TS on intraoral scans	91.0	-	-	-	-	-
TS and state assessment	-	-	98.9	-	95.5	-
TS (10 categories)	97.0	-	-	-	-	-
TS and root boundary extraction	97.3	98.45	93.35	-	92.97	93.01
TS (10 categories)	96.94	97.81	94.97	-	93.77	92.70

6. DISCUSSION

Significant advancements Using deep learning into the implementation of treatment of a variety of dental conditions such impacted or misaligned teeth, gingival difficulties, and periodontal concerns, dental arch abnormalities, or osteoporosis, were identified. Deep learning techniques have proven effective in facilitating rapid and accurate diagnosis of dental conditions.

C.N.N.s, with their ability to automatically extract important features from images, play a vital role in this domain. Faster R-CNN, Mask R-CNN, VGG, or YOLO are examples of pre-trained models that have demonstrated excellent performance. While Faster R-C.N.N is effective for teeth segmentation tasks, Mask R-CNN is particularly advantageous for identifying multiple regions of interest (ROIs) in different image types. YOLO, despite its strong performance in bitewing dental imaging, struggles with detecting small objects within images. VGG16, VGG19, ResNet50, ResNet101, DenseNet121, and InceptionV3 are common deep learning models that are frequently employed. Their integration has the potential to produce groundbreaking results.

Deep learning techniques are widely applied in classification, detection, and localization tasks, but segmentation remains particularly significant in medical imaging. For segmentation tasks, UNet is a widely utilized architecture consisting of two main paths: a contracting path and an expansive path. The contracting path functions as a standard CNN, while the expansive path utilizes transposed 2D convolutional layers to upsample the feature maps.

Evaluation Metrics

To evaluate model performance, measures including Precision, recall, Correctness, Sensitivity is Particularity, the F1- Score Dice Coefficients, Intersection-Over-Union (IOU), or Jaccard Index are employed.

7. CONCLUSION

Deep learning algorithms, particularly CNN-based approaches, offer reliable and accurate tools for dental image evaluation and disease diagnosis, significantly improving diagnostic accuracy and quickness. The results of this investigation show that these methods provide results comparable to those of dental professionals and radiologists.The proposed UNet, utilizing pre-trained models like ResNet-101 or DenseNet-101, demonstrated excellent segmentation performance for identifying dental issues and abnormalities. By incorporating skip connections, UNet effectively fuses features between encoder and decoder paths. However, its reliance on same-size feature maps and restricted fusion techniques poses limitations.

8. References

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