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A Robust Deep Learning Framework for Denoising Dental Radiographs to Support Precision Diagnosis in Medical Imaging

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Abstract-*Denoising medical images are essential for improving diagnostic accuracy by removing noise that obscures critical anatomical details. Dental radiographs are particularly vulnerable to noise from acquisition, transmission, or storage, affecting clinical interpretation. This study presents a hybrid deep learning framework integrating Convolutional Neural Networks (CNNs) and Transformer blocks for effective denoising of dental X-ray images. The CNN layers capture local structures such as teeth edges and bone morphology, while Transformer blocks model global contextual relationships to preserve fine details. Trained on Kaggle dental X-ray datasets with synthetic Gaussian noise, the model employs mini-batch optimization and data augmentation. Quantitative metrics, including PSNR and SSIM, demonstrate significant image enhancement, surpassing traditional denoising methods, supporting precise and confident dental diagnosis.*

1. INTRODUCTION

Medical imaging plays a pivotal role in modern healthcare by enabling non-invasive visualization of internal anatomical structures, supporting diagnosis, treatment planning, and disease monitoring. Among various imaging modalities, X-rays are widely employed due to their accessibility, speed, and capability to capture high-resolution structural details. In dental practice, radiographs are crucial for identifying cavities, periodontal diseases, root fractures, bone loss, and other oral conditions. However, image quality is often degraded by noise introduced during acquisition, transmission, or storage, which can obscure fine anatomical details and lead to misinterpretation or misdiagnosis. Noise in dental radiographs may result from low exposure settings, sensor limitations, patient movement, or environmental interference. Conventional denoising techniques, such as Gaussian or median filtering and wavelet-based methods, are commonly used to mitigate noise but tend to blur critical structures, including tooth edges, root canals, and bone morphology, reducing diagnostic reliability.

Recent advances in deep learning have transformed image processing across multiple domains, including medical imaging. Convolutional Neural Networks (CNNs) have demonstrated remarkable capabilities in feature extraction, image enhancement, and classification due to their ability to learn hierarchical representations directly from data. Autoencoder-based CNNs have been particularly effective for image denoising, mapping noisy inputs to clean outputs while preserving essential structures. However, CNNs often struggle to capture long-range dependencies crucial for maintaining global structural consistency. Transformers, originally developed for natural language processing, employ self-attention mechanisms to model global relationships, complementing CNNs' local feature extraction. By integrating CNNs and Transformers in a hybrid framework, it becomes possible to achieve both local detail preservation and global contextual modeling. This study develops such a framework for denoising dental radiographs, aiming to suppress noise while maintaining anatomical fidelity, thereby improving diagnostic accuracy and supporting clinical decision-making.

2. PROBLEM STATEMENT

Dental radiographs are essential for accurate diagnosis and treatment planning, yet they are often degraded by noise introduced during image acquisition, transmission, or storage. Such noise can obscure critical anatomical details, including tooth edges, root canals, and bone structures, complicating clinical interpretation. Conventional denoising techniques, such as median filtering and Gaussian smoothing, reduce noise but frequently compromise important features, leading to potential loss of diagnostic information. This limitation underscores the need for an advanced denoising solution capable of effectively suppressing noise while preserving fine structural details, ensuring high-quality dental images that support precise and reliable clinical decision-making.

3. OBJECTIVES

The primary objective of this study is to develop a robust hybrid CNN-Transformer framework for denoising dental radiographs, effectively reducing noise while preserving essential anatomical structures such as tooth edges, root canals, and surrounding bone. The model is trained on a dental X-ray dataset from Kaggle, with synthetic noise added to replicate real-world imaging conditions. Performance is assessed using metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) to ensure superior denoising compared to conventional methods. Additionally, the study aims to deploy the trained model through a Flask-based web application, offering dental professionals a convenient, real-time tool to enhance image quality and support accurate clinical decision-making.

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4. METHODOLOGY

1) Data Collection: The dataset for this project consists of dental X-ray images sourced from Kaggle, a widely recognized platform for open medical imaging datasets. Images were selected to represent diverse dental structures, including teeth, roots, and surrounding bone regions. In cases where clean ground-truth images were unavailable, synthetic noise, such as Gaussian noise, was added to generate paired noisy-clean datasets suitable for supervised learning. This dataset forms the basis for training, validation, and testing, ensuring robustness across varying imaging conditions.

2) Data Pre-processing: Pre-processing standardizes the images for model training. Each X-ray image was resized to a fixed resolution and converted to grayscale to reduce computational complexity. Pixel values were normalized between 0 and 1, facilitating stable model convergence. Data augmentation techniques, including rotations, flips, and zooming, were applied to increase dataset diversity and enhance the generalization capability of the model.

3) Feature Extraction: Feature extraction is performed by the convolutional layers of the network, which learn hierarchical representations of input images. Local anatomical structures, such as tooth edges, root canals, and bone boundaries, are captured through successive convolution and pooling operations. Transformer blocks then analyze these features to model global contextual relationships across the entire image.

4) Model Selection: Hybrid CNN-Transformer architecture was chosen for its ability to leverage both local and global features. A convolutional autoencoder serves as the backbone, efficiently compressing and reconstructing images. Transformer blocks are incorporated to model long-range dependencies and refine global contextual information, achieving superior denoising performance while preserving anatomical details.

5) Model Training: The model is trained in a supervised manner using paired noisy and clean images. Mean Squared Error (MSE) is used as the loss function to minimize differences between predicted denoised outputs and ground truth. Training employs mini-batches with the Adam optimizer, along with early stopping and learning rate scheduling to improve convergence. Validation data monitors performance and prevents overfitting.

6) Model Evaluation: Model performance is assessed using quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), which evaluate image clarity and structural fidelity. Visual inspection is also performed to confirm retention of fine anatomical details. Comparisons with traditional denoising methods, including median and Gaussian filtering, demonstrate superior performance of the hybrid CNN-Transformer model. Epoch-wise tracking of PSNR and SSIM further validates consistent improvement throughout training.

7) Integration with Flask: For practical deployment, the denoising model is integrated into a Flask web application. Users can upload noisy dental X-rays, which the model processes to generate enhanced outputs in real time. The interface allows dental professionals to visually inspect results immediately and can be incorporated into hospital imaging systems for streamlined clinical workflows and decision support.

5. LITERATURE SURVEY

Dental X-ray images often contain unwanted noise that affects image clarity and reduces diagnostic quality. Earlier image enhancement methods were able to remove some noise, but they also caused loss of important details in the radiographs. Because of these limitations, researchers have focused on artificial intelligence and deep learning techniques for image denoising.

Different deep learning models such as convolutional neural networks, Transformer networks, GANs, and U-Net architectures have shown strong performance in improving dental radiographs. These models can reduce noise while preserving essential structures like teeth edges, roots, and bone regions. Hybrid approaches that combine CNN and Transformer techniques provide better image enhancement by learning both local and global features from the images.

6. SYSTEM DESIGN

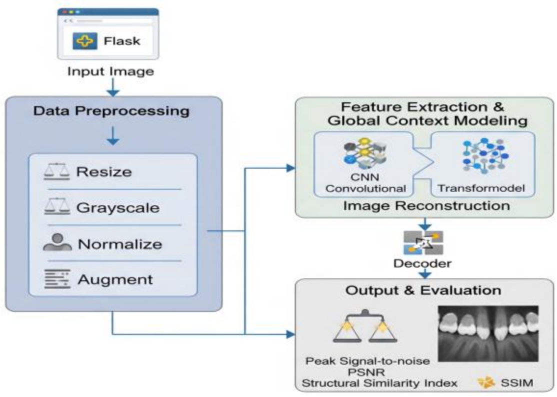

Figure 1: System Architecture of Denoise image

The system architecture of the hybrid CNN-Transformer framework for dental radiograph denoising is designed to enhance noisy X-ray images, supporting precise clinical diagnosis. Users upload dental X-rays through a Flask web interface, compatible with standard formats such as JPEG and PNG. Uploaded images undergo preprocessing, including resizing, grayscale conversion, normalization, and data augmentation, to prepare them for model input. CNN layers perform feature extraction, capturing local anatomical details such as tooth edges, root canals, and bone structures, while Transformer blocks model global contextual relationships to preserve structural coherence across the image. The decoder then reconstructs the denoised output, maintaining fine anatomical details. The enhanced images are displayed via the web interface, and quantitative metrics like PSNR and SSIM are calculated to assess model performance. This architecture enables efficient, accurate, and real-time image enhancement for clinical applications.

7. SCREENSHOTS

1. Home page

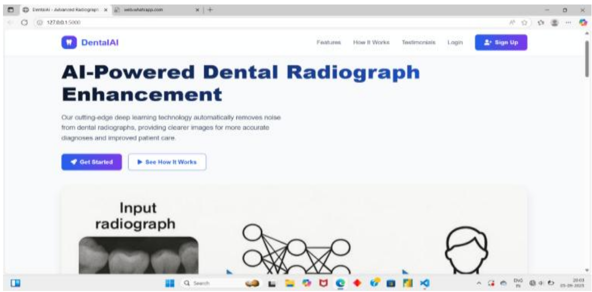

Figure 2: Home page

2. Select Image

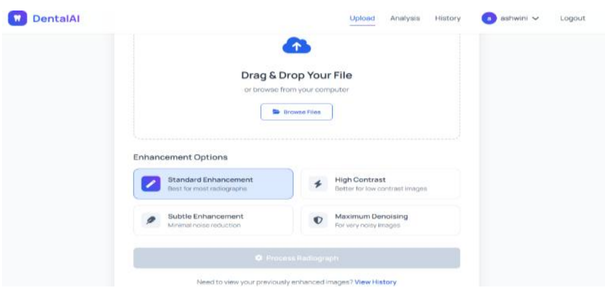

Figure 3: Selecting Image

3. Enhancement Results & Analysis

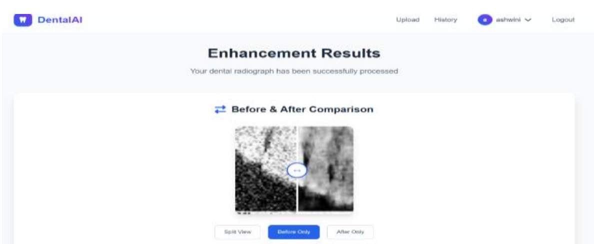

Figure 4: Enhancement Results & Analysis

8. CONCLUSION & FUTURE SCOPE

In this research, a robust deep learning framework was developed to enhance dental X-ray images, enabling more accurate diagnostic interpretation. Leveraging hybrid CNN-Transformer architecture, the system effectively reduces noise while preserving critical anatomical structures, including tooth edges, root canals, and bone details. The model was trained and validated on dental X-ray datasets from Kaggle, with synthetic noise added to simulate real-world imaging conditions. A Flask-based web interface allows users to upload, view, and download denoised images seamlessly. Performance evaluation using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) demonstrated significant improvements in image clarity, while visual inspection confirmed preservation of essential diagnostic features. Compared to conventional methods like median and Gaussian filtering, the proposed approach delivers superior noise suppression without blurring key structures, enhancing diagnostic confidence and treatment planning.

For future improvements, expanding the dataset to include a wider variety of real-world noisy-clean images from multiple clinics would enhance generalization across diverse patients and imaging conditions. Incorporating deeper CNN layers, additional Transformer blocks, or attention mechanisms can improve detection of subtle anatomical details. Upgrading the Flask interface for real-time batch processing, cloud integration, and EHR compatibility, along with automated quality feedback using PSNR and SSIM, would further increase usability. These enhancements can transform the system into a comprehensive, intelligent assistant for dental diagnostics, improving accuracy, efficiency, and accessibility in clinical workflows.

9. REFERENCES

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