Dental Image Segmentation and Classification of Dental Conditions

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ABSTRACT

Dental X-rays are widely used for diagnosing oral health conditions, but manual interpretation is often time-consuming and subject to human error. This workfocuses on developing an automated system for segmentation and classification of periapical and panoramic dental X-ray images . The segmentation phase isolates teeth and other relevant structures to enhance clarity and facilitate diagnosis. Accurate segmentation is crucial for ensuring precise classification and improving the interpretability of the images. Following segmentation, the classification module categorizes dental conditions based on extracted features, helping dentists identify abnormalities such as cavities, root fractures, or periapical lesions more efficiently. The system is trained and tested on a dataset of annotated periapical X-ray images and is evaluated based on accuracy, precision, recall, and F1-score. By automating the segmentation and classification process, this approach minimizes diagnostic inconsistencies and reduces the workload of dental professionals. Additionally, it enhances treatment planning, ultimately improving patient outcomes. The proposed system aims to provide a accurate and reliable tool for dental radiographic analysis, ensuring a faster and more consistent evaluation of periapical X-rays in clinical settings.

Keywords: Periapical Dental Xray Images, Panoramic Dental X-Ray Images, Dental Radiographic Analysis, Segmentation, Classification

INTRODUCTION

Dental imaging plays a vital role in modern dentistry, aiding in the diagnosis and treatment of various oral health conditions. Panoramic and periapical X-rays are widely used for dental assessments, with panoramic images providing a broad view of the entire dentition and jaw, while periapical images offer detailed insights into individual teeth and their surrounding structures. These imaging techniques are essential for detecting conditions such as cavities, root fractures, periodontal diseases, and other abnormalities. Traditionally, dentists manually interpret these images, a process that can be time-consuming, subjective, and prone to human error.

Variations in experience and visual assessment can lead to inconsistent diagnoses, affecting treatment decisions. To overcome these challenges, automated image processing techniques provide a more efficient, consistent, and accurate approach to dental radiographic analysis. This project aims to develop an automated system for the segmentation of both panoramic and periapical dental X-ray images, along with classification of periapical X-rays for disease prediction. The segmentation phase focuses on extracting teeth and other relevant structures to enhance image clarity and interpretability. The classification module analyses the segmented periapical regions to identify dental conditions, assisting dentists in making more precise and reliable diagnoses.

SIGNIFICANCE OF THE PROJECT

- **Enhanced Diagnostic Accuracy:** Reduces human error and ensures more reliable identification of dental conditions.
- **Improved Efficiency**: Automates segmentation and classification, minimizing the time required for manual analysis.
- **Comprehensive Analysis:** Supports both panoramic and periapical X-ray segmentation, offering a broader and detailed assessment.
- **Reduced Workload for Dentists:** Assists dental professionals by automating repetitive tasks, allowing them to focus on critical cases.

Objectives

This project aims to develop an automated system for analyzing dental X-ray images by integrating segmentation and classification. Working with both panoramic and periapical X-rays, the system enhances diagnostic accuracy and supports efficient treatment planning.

Specific Objectives:

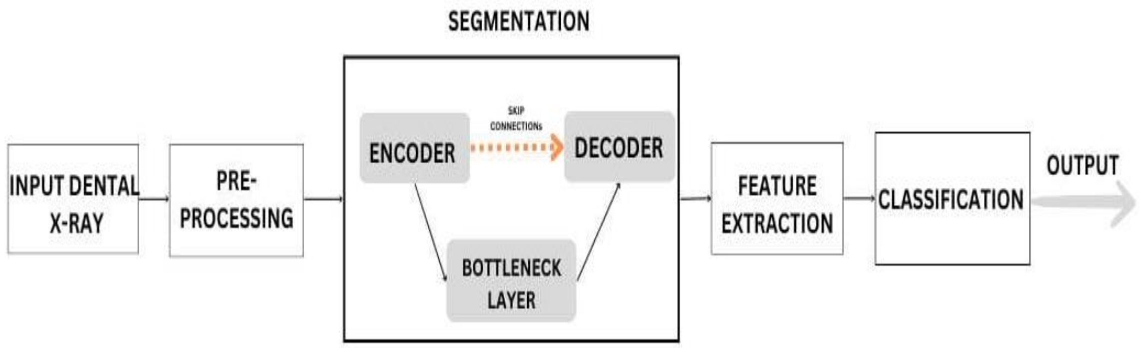
Accurate Tooth Segmentation: Develop a robust segmentation model to precisely distinguish teeth from surrounding structures, improving clarity for better identification of dental abnormalities.

Dental Condition Classification: Classify dental conditions such as cavities, fractures, root infections, and periodontal diseases to support early detection and treatment.

Integrated Diagnostic System: Combine segmentation and classification into a unified system, streamlining workflow and providing structured outputs for faster and more reliable diagnosis.

METHODOLOGY

The methodology is structured into three main stages: Dental X-ray Segmentation, Health Status Classification, and Integration of Segmentation and Classification. These steps ensure accurate identification and analysis of teeth while providing a reliable framework for evaluating dental conditions.



Dental X-ray Segmentation
Segmentation is a crucial step in analyzing dental X-rays, as it isolates individual teeth from surrounding structures. This process is applied to both panoramic and periapical X-ray images to extract meaningful tooth regions while excluding irrelevant areas such as the jawbone and soft tissue.

Segmentation Approach:
A model is trained on labeled datasets to distinguish teeth from the background and separate them accurately. It learns the structural features of teeth, including their shape, position, and contrast differences within the X-ray. The segmentation model processes the input X-ray and generates a mask that highlights individual teeth while preserving important anatomical details.

Segmentation Output:
Once processed, the system generates a segmented image where each tooth is distinctly outlined. This serves as a foundation for further analysis, particularly for classification in periapical X-rays.

Health Status Classification
In periapical X-ray images, after obtaining segmented teeth, the next step is classification, where each tooth is analyzed to determine its condition. The classification model is trained using labeled data, where different dental conditions are annotated based on visual and structural characteristics.

Feature Extraction for Classification:
The classification model relies on specific features extracted from each segmented tooth. Key features used for differentiation include:

- **Shape and Contour:** Irregularities in shape may indicate fractures or damage. Texture and Density Patterns: Areas with reduced density often indicate decay or bone loss.

- **Structural Integrity:** Disruptions in the tooth structure can suggest root fractures or infections.

Differentiation of Dental Conditions:
The classification model analyzes extracted features to categorize teeth into different conditions:

- **Dental Decay:** Appears as dark, demineralized regions within the tooth, often located at the enamel-dentin junction.
- **Fractures:** Identified by sharp, linear breaks within the tooth structure, sometimes extending to the root.
- **Root Canal Infections:** Characterized by radiolucent (dark) areas around the root apex, indicating possible infection.
- **Periodontal Diseases:** Recognized by irregular bone loss patterns and increased spacing between the tooth and surrounding bone.

Classification Output:
The classification model assigns a label to each segmented tooth in periapical X-rays, indicating its condition. This output helps in assessing potential dental issues and supports decision-making in clinical settings.

Integration of Segmentation and Classification
To ensure a streamlined workflow, segmentation and classification are integrated into a single pipeline. This combined approach allows efficient processing of dental X-rays while maintaining accuracy in both segmentation and condition identification.

Processing Flow:

- For panoramic X-rays, the model focuses solely on segmentation, extracting clear boundaries for each tooth.
- For periapical X-rays, segmentation is followed by classification, where each segmented tooth is analysed for its health status.

Ensuring Accuracy and Consistency:
The integrated system is designed to maintain high diagnostic accuracy by aligning segmentation output with classification input. This ensures that condition assessment is performed on well-defined tooth regions, minimizing errors in analysis.

This methodology provides a structured and efficient approach for analyzing dental X-rays, improving diagnostic consistency, and assisting in better clinical decision-making.

System Overview

The system processes dental X-rays to isolate individual teeth through segmentation, extracts relevant features, and classifies dental conditions based on these extracted features. The approach integrates U-Net for segmentation and MLP for classification, ensuring precise identification of tooth structures and their conditions.

Input Data
The system utilizes two types of dental X-ray datasets, ensuring diverse data sources for both segmentation and classification tasks:

Panoramic X-ray dataset :

- Consists of 598 grayscale images.
- Each image has a resolution of 1018 × 506 pixels.
- Provides a detailed view of the entire dentition, including teeth, jawbones, and surrounding structures.
- Each image has a corresponding segmentation mask in PNG format, outlining individual teeth.

Periapical X-ray dataset :

- Contains 929 grayscale images collected from dental clinics, ensuring real-world diversity.
- Provides high-resolution views of individual teeth and surrounding structures.
- Stored in JPEG and PNG formats, making them compatible with standard image processing tools

Tooth Segmentation Using U-Net
Tooth segmentation is a crucial step in this system, enabling the isolation of individual teeth from X-ray images. The U-Net model is employed due to its effectiveness in biomedical image segmentation. It follows an encoder-decoder

architecture that processes input images to generate precise segmentation masks.The encoder (contracting path) extracts features by passing the input image through multiple convolutional layers. Each layer consists of a 3×3 convolution, ReLU activation, and batch normalization to stabilize training. Max pooling layers progressively reduce the spatial dimensions, allowing the model to capture high-level features while maintaining computational efficiency. As the depth increases, the encoder learns hierarchical representations, enabling better understanding of tooth structures.At the center of the architecture, the bottleneck (bridge layer) serves as a transition between encoding and decoding.

Additional convolutional layers refine the extracted features, ensuring that essential information is preserved before reconstruction.The decoder (expanding path) reconstructs the segmented image using upsampling layers, which restore spatial resolution. Each upsampling operation is followed by 3×3 convolutions and ReLU activation, gradually refining the segmented output. The decoder is aided by skip connections, which directly transfer fine-grained spatial details from the encoder to corresponding layers in the decoder. These connections help maintain structural integrity and improve segmentation accuracy. The final output of the U-Net model is a binary segmentation mask, highlighting individual teeth while separating them from the background.

Feature Extraction for Classification

Once the teeth are segmented, meaningful features are extracted to facilitate classification. This involves analyzing texture, shape, and structural properties using three feature extraction techniques:

Gray-Level Co-occurrence Matrix (GLCM) is used to capture texture properties by analyzing the spatial relationships between pixel intensities within the segmented region. It computes statistical features such as contrast, correlation, energy, and homogeneity, which describe variations in pixel intensity patterns. These features are useful in differentiating textures associated with various tooth conditions.

Histogram of Oriented Gradients (HOG) extracts shape-based features by analyzing gradients in the segmented region. It focuses on edge orientations and intensity changes, capturing structural information relevant to dental conditions. The method involves computing gradient magnitudes and orientations, followed by binning these values into histograms, which serve as the feature descriptors.

Local Binary Pattern (LBP) captures fine-grained texture variations by comparing pixel intensities in a local neighborhood. Each pixel in the segmented region is assigned a binary code based on intensity differences with its neighbors. The resulting binary patterns describe micro-level texture characteristics, aiding in distinguishing different dental conditions.

Feature Normalization and Dimensionality Reduction

Since the extracted features vary in magnitude and scale, normalization is necessary to ensure consistency. Min-Max Scaling is applied to transform all feature values into a uniform range of 0 to 1, preventing bias toward features with larger values.

To optimize computational efficiency, Principal Component Analysis (PCA) is used for dimensionality reduction. PCA identifies the most significant components within the extracted feature set, eliminating redundant information while retaining the most informative aspects. This reduces the overall number of features, leading to faster and more effective classification.

Classification Using Multilayer Perceptron (MLP)

The classification model is implemented using a Multilayer Perceptron (MLP), which processes the extracted features and determines the condition of the segmented tooth.

The input layer receives the normalized feature vector, which consists of texture, shape, and structural descriptors obtained from feature extraction. This feature vector serves as the input for the subsequent layers of the network.

The hidden layers are responsible for learning complex relationships within the feature set. Each hidden layer consists of multiple neurons that apply weighted summation, followed by an activation function. ReLU activation is used in these layers to introduce non-linearity, allowing the network to capture intricate patterns within the data. The hidden layers refine the extracted features, ensuring accurate classification.

The output layer produces the final classification result. It consists of a set of neurons, each representing a possible category. The output layer assigns a classification label to the input based on the learned patterns.

Output Generation

The system provides two types of outputs:
Segmentation Output: Displays the segmented X-ray image, highlighting individual teeth.
Classification Output: Indicates the condition of the segmented tooth based on extracted features.

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These outputs enable automated analysis of dental X-rays, aiding in efficient diagnosis and research.

Software Requirements

The tooth segmentation and classification system is implemented using MATLAB 2024a, a powerful environment for image processing, deep learning, and machine learning.

MATLAB 2024a: Provides a robust framework for medical image analysis, neural network training, and algorithm development.

Deep Learning Toolbox: Facilitates the implementation and training of the U-Net model for segmentation, offering prebuilt architectures and real-time training monitoring.

Image Processing Toolbox: Enhances X-ray images through grayscale conversion, contrast adjustments, and morphological operations to improve segmentation accuracy.

Computer Vision Toolbox: Extracts essential features (HOG, LBP) from segmented tooth regions, aiding in disease classification.

Statistics and Machine Learning Toolbox: Supports dimensionality reduction (PCA) and implements an MLP classifier for accurate dental condition prediction.

RESULTS

The developed system successfully segmented periapical and panoramic dental X-ray images using the U-Net model, effectively distinguishing dental structures for further analysis. The segmentation results provided clear delineation of regions of interest, enabling better feature extraction for classification. The classification model offered valuable insights into different dental conditions, contributing to a more structured and automated diagnostic process. While the results indicate strong potential, further refinements in feature extraction and model optimization can enhance overall accuracy and reliability. The system demonstrates promise in supporting dental professionals by reducing manual effort and improving diagnostic consistency.

i) Segmentation

Segmentation Performance Evaluation

Metric	Value
Precision	91.7%
Recall	88.68%
F1-Score	90.19%
IoU	80.90%

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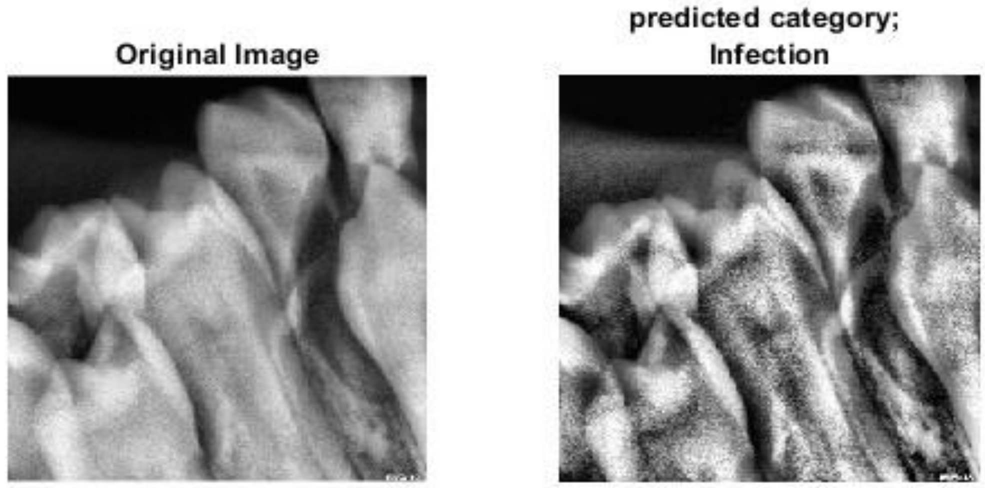
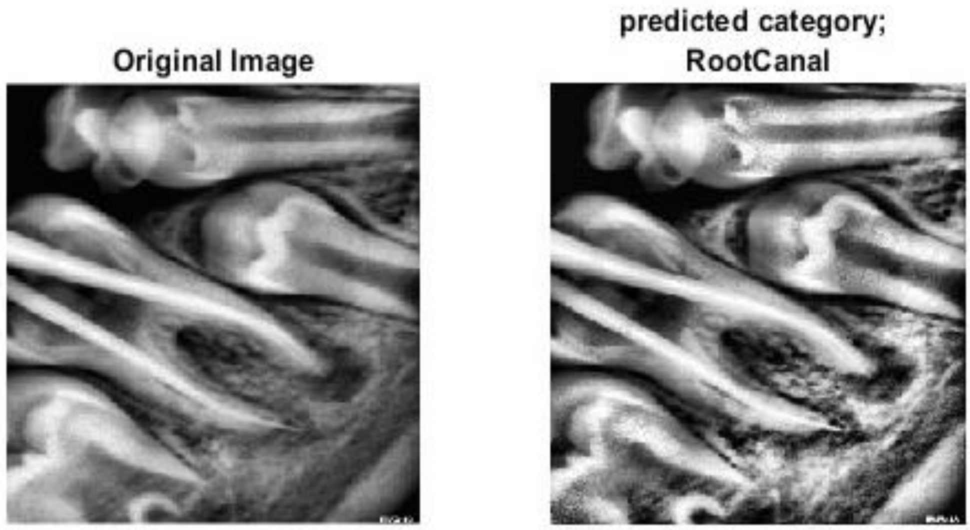
ii) Classification Of Periapical Xray



a)



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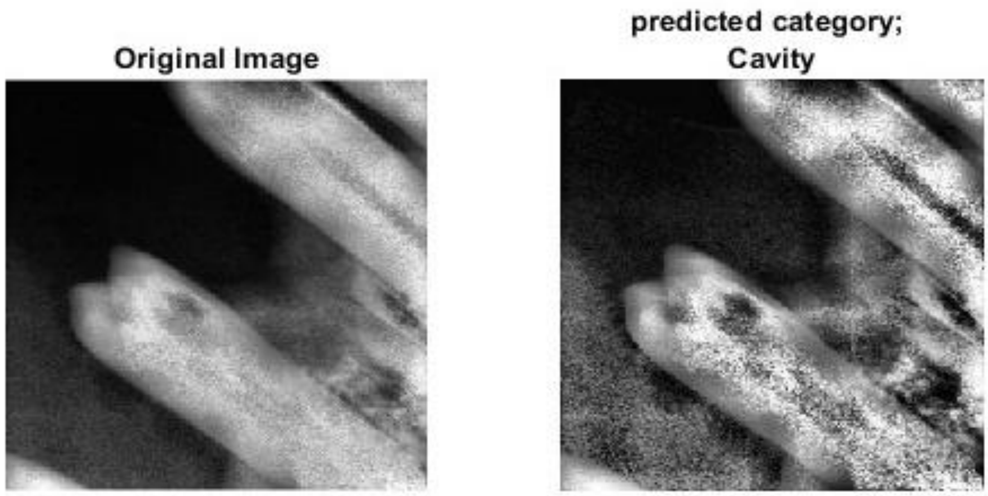

c)

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Classification Performance Parameters

Metric	Value
Precision	97.85%
Recall	98.75%
F1-Score	98.04%
Accuracy	97.87%

d) Segmentation Performance Evaluation

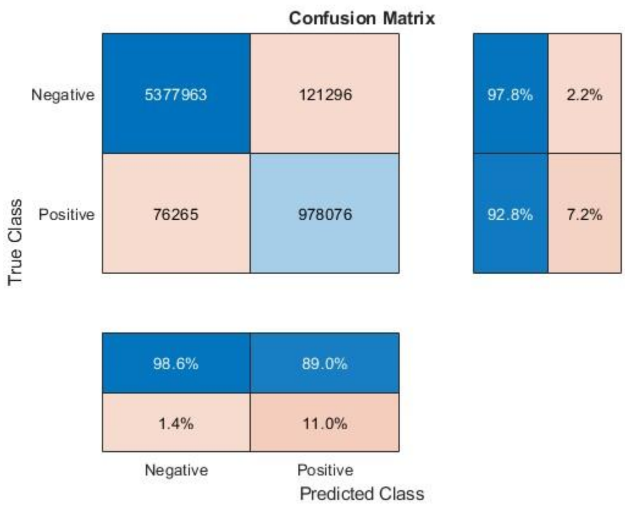
CONFUSION MATRIX

i) Segmentation

A confusion matrix is a performance evaluation. It provides insight into the model's accuracy, precision, recall, and error distribution.

The matrix consists of four key values:

- **True Negatives (TN) :**Cases correctly predicted as negative.
- **False Positives (FP):** Cases incorrectly predicted as positive when they are actually negative (Type I error).
- **False Negatives (FN) :** Cases incorrectly predicted as negative when they are actually positive (Type II error).
- **True Positives (TP) :**Cases correctly predicted as positive.



Confusion Matrix

ii) Classification

1. Training Confusion Matrix

Purpose: Evaluates how well the model learned from the training data.

Observation: Most predictions are accurate, indicated by the high values on the diagonal.Misclassifications (off-diagonal) are minimal, meaning the model fit well to the training data.

Possible Concern: Extremely low error during training may indicate overfitting if not matched by good validation and test results.

2. Validation Confusion Matrix

Purpose: Tests the model's generalization capability using unseen validation data.

Observation: Slightly more misclassifications compared to the training set, which is expected.If the accuracy drop is significant, it could mean the model is overfitting.Some classes may have more confusion than others, indicating areas for improvement.

Action: Adjust hyperparameters or apply regularization if validation accuracy is poor.

3. Test Confusion Matrix

Purpose: Assesses the model's final performance on unseen test data, simulating real-world scenarios.

Observation: The performance is generally lower than on training and validation sets. Misclassifications are visible, particularly for certain classes. If the performance is consistent with validation results, it means the model has good generalization.

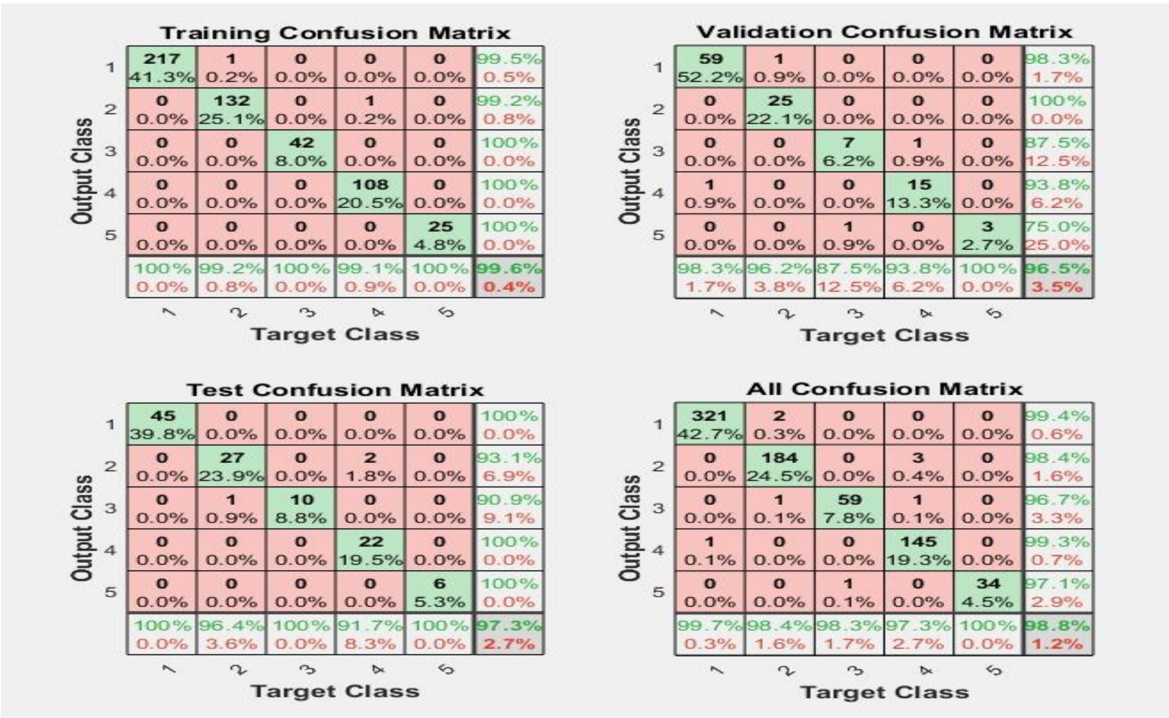
Action: If there is a large drop from validation to test accuracy, further testing or more balanced data may be required.

4. Overall Confusion Matrix

Purpose: Provides a combined view of training, validation, and test results to evaluate general performance.

Observation: High accuracy on the diagonal suggests strong overall model performance. Misclassifications are highlighted, helping identify problematic classes.

Action: If specific classes show consistent misclassifications, it may require data rebalancing or additional features for better classification.

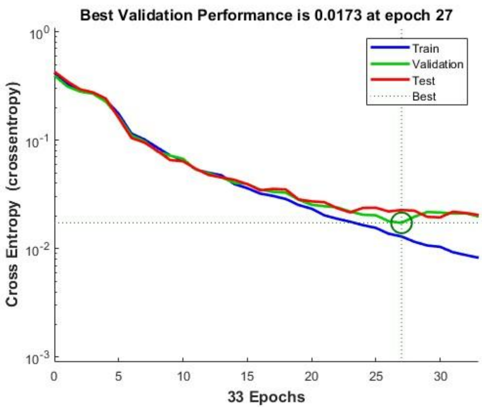


Confusion Matrix

Classification performance plot

This figure shows the performance of the dental disease classification model across training, validation, and test datasets using cross-entropy loss as the performance metric. The best validation performance of 0.011259 was achieved at epoch 41, as indicated by the green circle. The training loss continues to decrease, while the validation and test losses show stabilization, demonstrating good generalization of the model.

Performance Plot



CONCLUSION

The project aims to develop an innovative automated system for the segmentation and classification of dental conditions using dental X-ray images. By employing a precise tooth segmentation model, followed by a robust classification model, we seek to enhance the diagnostic capabilities for dental professionals. The approach promises to automate the analysis of X-rays, improving both accuracy and efficiency in identifying conditions such as cavity, fracture, periodontal disease etc.The model can be further expanded to detect a wider range of dental conditions.Further improvements in dataset diversity and real-time processing can enhance practical applicability.

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