“A Comprehensive Deep Learning Framework for Dental Disease Classification”

Summarization

Introduction

Related to the task purpose, I used this paper to take a model for using it in my code. It discussed the results of 5 different Deep Learning models for automated detection of common dental diseases (5-CNN Layer Model, EfficientNet Model, ResNet-50 Model, ViT Model, 3-CNN Layer Model), to analyze dental images and classify them into five prevalent classes (Dataset contains 5 dental classes).

Trained on a dataset split into 70% training, 15% validation, and 15% testing, the model achieved a validation accuracy of **87.6%**. The proposed system incorporates data augmentation to enhance generalization, confidence thresholding to identify uncertain cases, and a user-friendly web interface.The optimal hyperparameters identified include a learning rate of 0.0001, batch size of 32, and Adam optimizer, which provided the best trade-off between stability and training speed.

Dataset description

The dataset used in this study consists of 10,573 clinically sourced dental images; it provides a comprehensive foundation for training, validating, and testing. The images are categorized into five distinct dental conditions: caries (2,382 images), gingivitis (2,349 images), hypodontia (1,251 images), mouth ulcers (2,541 images), and tooth discoloration (2,050 images). The dataset was partitioned into three subsets: 70% (7,399 images) for training, 15% (1,585 images) for validation, and 15% (1,589 images) for testing. The images, saved in JPEG format, were preprocessed to conform to an input shape of 224 × 224 pixels with three color channels (RGB).

Data preprocessing

Image resizing: To standardize the input for the model, all dental images are resized to dimensions of 224 × 224 pixels. Image resizing reduces the variability in image size without compromising critical features necessary for disease classification.

Pixel value normalization: All pixel values are normalized to a range of [0, 1] to standardize input intensity, ensuring consistent model performance.

Data augmentation: To mitigate overfitting and enhance the robustness of the model, data augmentation techniques are employed. These methods artificially expand the dataset by introducing variations in the images while preserving their core characteristics [19, 20].

Model Architecture

Input layer

Input Resolution: 224×224×3224 \times 224 \times 3224×224×3 (RGB format).Preprocessing included real-time data augmentation and normalization as outlined above.

Convolutional layers

Each convolutional layer applied a filter bank to extract features .

Pooling and dropout

Max-pooling layers (2×22 \times 22×2) reduced the spatial dimensions by a factor of 2, facilitating feature abstraction while preventing overfitting through dropout regularization.

Fully connected layers

The dense layers transformed the high-dimensional feature maps into class probabilities. The final dense layer employed the **Softmax** activation function. To enhance the robustness and effectiveness of our dental disease classification model, we incorporated two additional state-of-the-art deep learning architectures: **ResNet** and Vision Transformer (ViT). **ResNet** (Residual Networks) is designed to mitigate the vanishing gradient problem, enabling deep feature extraction with residual connections.

Both the 5-layer CNN and ViT achieved the highest accuracy of 87.6%, followed closely by ResNet-50 and EfficientNet. ViT provided superior feature extraction capabilities due to its attention-based mechanism, whereas CNNs, particularly **ResNet**, effectively captured hierarchical spatial patterns.

Results and Discussion

The performance of the proposed 5-layer CNN was thoroughly evaluated against multiple deep learning architectures, including 3-layer CNN, EfficientNet, ResNet 50, and Vision Transformer (ViT). The 5-layer CNN demonstrated its effectiveness in dental disease classification with a validation accuracy of 87.61%, significantly improving from an initial training accuracy of 68.15% to 86.69% across 25 epochs. The validation loss also declined from 0.7729 to 0.5347, indicating stable convergence.

ResNet-50: Achieved high accuracy due to residual connections, preventing vanishing gradient issues in deeper architectures.

Conclusion

The Dental Disease Detection System effectively demonstrates the integration of artificial intelligence into dental healthcare, providing a robust solution for automated diagnosis of multiple dental conditions. The model achieved an impressive final validation accuracy of 82.21% and training accuracy of 86.69% after 19 epochs, underscoring its efficacy in extracting meaningful features from dental images. The systematic reduction in loss values, from 0.8086 to 0.3654, further highlights the model's reliable convergence and learning efficiency.

Reference

[1] Parkhi, P., Harjal, S., Sahu, A., Agrawal, P., Shingne, H., Bobde, Y., & Padole, A. (2025). A Comprehensive Deep Learning Framework for Dental Disease Classification. *Journal Européen des Systèmes Automatisés*, *58*(3).

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