

Teeth Classification Project Report

Overview:

This project focuses on developing a deep learning model for classifying dental images into seven distinct categories related to oral health conditions. The categories are: ['CaS', 'CoS', 'Gum', 'MC', 'OC', 'OLP', 'OT'].

Data Loading and Preprocessing:

- Loading: using `tf.keras.utils.image_dataset_from_directory` for train/validation/test splits.
- Preprocessing: through Normalization (by rescaling) and data augmentation (using `RandomFlip`, `RandomRotation`, `RandomZoom` and `RandomTranslation`).

Visualizations:

- Distribution: MC and OC have the highest number of samples while OC and Gum have the lower number of samples but the training data is reasonably balanced.
- Visualization before and after augmentation: after using the `data_augmentation` we save each image with its augmented one in a folder in `visualization_outputs`.
- Histogram of Pixel Intensities for each of the 3 channels (RGB): Distinct color profiles per class, explain the model's effectiveness, as RGB features are discriminative.
- Sobel Edge Maps: method used to identify edges in an image by detecting areas of rapid intensity changes, highlights boundaries between objects or regions with different brightness levels and the outputs are saved in a folder in `visualization_outputs`.

- Dimensionality Reduction (t-SNE): reduces high-dimensional ResNet features to 2D for visualizing class clusters

Model Training:

- The model was trained for 50 epochs using categorical cross-entropy loss (with label smoothing) and the Adam optimizer. The architecture consisted of X convolutional layers (Conv2D + BatchNormalization + MaxPooling combinations), followed by fully connected Dense layers. A Dropout strategy was applied for regularization (0.5 and 0.3), and L2 weight regularization (`tf.keras.regularizers.l2(0.001)`) was used on some layers to reduce overfitting.
- A training log file was also generated to record model performance (loss, accuracy, and validation metrics) across epochs for reproducibility and debugging

Evaluation of Test Results:

The model achieved 95% accuracy on the held-out test dataset, which confirms its strong generalization ability.

- Confusion Matrix: showed most predictions aligned with the correct classes (strong diagonal dominance), meaning the model rarely confused different conditions.
- Classification Report: confirmed balanced performance across classes, with precision, recall, and F1-scores all above 0.90 for most categories.

The evaluation highlights the robustness of the model while also pointing out biologically relevant challenges in distinguishing similar oral diseases.

Future Improvements:

- Model Architecture: Experimenting with deeper CNNs.

- Deployment: Building a lightweight web or mobile app to assist dentists in real-time clinical settings.