Automated Classification of Dental and Gum Diseases Using Convolutional Neural Networks: A Practical Study

# Abstract

In this study, a deep learning approach was proposed to classify dental and gum disease images into multiple categories using a Convolutional Neural Network (CNN). The initial dataset suffered from imbalance and inconsistency in the number of images per class, which negatively affected the model’s performance. Data augmentation techniques were applied to address the issue. Additionally, various model optimization techniques such as dropout regularization, filter size adjustments, and tuning batch size and number of epochs were investigated. Results show a noticeable improvement in accuracy from 53% to 69%.

# 1. Introduction

Dental diseases and gum conditions can be diagnosed through image analysis of the oral cavity. Early detection improves treatment outcomes and reduces medical risks. With the rapid growth of computer vision and deep learning, automated image-based disease classification has become achievable. Convolutional Neural Networks (CNN) are especially effective in processing and classifying image data.  
  
This paper presents a practical implementation of a CNN model to classify dental and gum disease images into seven categories, discussing the challenges faced, solutions applied, and model performance evaluation.

# 2. Problem Description

The dataset initially contained an inconsistent number of images per class in the training, validation, and test sets, causing a data imbalance problem. Furthermore, the model initially exhibited overfitting, achieving a 53% accuracy on validation data while performing better on training data. Overfitting occurs when the model memorizes training data without effectively generalizing to new, unseen data.

# 3. Methodology

## 3.1 Data Preparation

The dataset included images of seven disease categories: Cas, CoS, Gum, MC, OC, OLP, and OT. Data augmentation techniques were applied to balance the number of images per class and increase data variety. The augmentation included:  
- Rotation  
- Zoom  
- Horizontal and vertical flips  
- Brightness adjustments  
  
Normalization was applied to scale pixel values between 0 and 1.

## 3.2 Model Architecture

The initial CNN model consisted of:  
- Convolutional layers with ReLU activation  
- MaxPooling layers  
- Flatten layer  
- Fully connected (Dense) layer  
- Softmax output layer  
  
Dropout layers were added to reduce overfitting.

## 3.3 Optimization

As the initial model showed overfitting with 53% accuracy, several adjustments were made:  
- Modified filter sizes in convolutional layers  
- Tuned the batch size for better gradient updates  
- Increased the number of epochs for better convergence  
  
These changes improved the final accuracy to 69%.

# 4. Results and Discussion

The model’s accuracy improved significantly after balancing the dataset and adjusting model parameters. While dropout regularization alone did not effectively address overfitting, increasing filter sizes and optimizing batch size and epochs provided substantial gains.  
  
A comparison of model accuracy before and after optimization is summarized in the table below:

|  |  |
| --- | --- |
| Configuration | Accuracy (%) |
| Initial Model (with Dropout) | 53 |
| Adjusted Filters & Parameters | 69 |

# 5. Conclusion

This study demonstrates the importance of balanced datasets, appropriate data augmentation, and model optimization in improving deep learning performance in medical image classification tasks. Future work includes experimenting with transfer learning using pre-trained CNN models and implementing visualization techniques like Grad-CAM to interpret model decisions.