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Periodontal Disease Classification with Color Teeth Images Using Convolutional Neural Networks

tags :

Paper summarization for Teeth task

Summary of the Abstract:

This paper highlights the importance of oral health and introduces a **deep learning model** designed to detect **periodontal diseases** (gum diseases) using **RGB (color) mouth images** instead of traditional X-rays. The authors developed a **custom CNN architecture** using **parallel 1D convolutions** and found it outperformed standard models like **ResNet152** by **11.45%**, especially when training data is limited. This suggests that **optical images from normal cameras** could be used for **mobile oral health diagnosis** in the future.

1. Introduction

- Oral health significantly impacts overall quality of life, especially daily functions like eating, speaking, and smiling. Recently, **AI-powered oral healthcare systems** have gained attention. However, most existing research relies on **dental panoramic X-rays** (DPR) to perform tasks like **tooth identification (numbering)** and **dental disease detection**. Early efforts used periapical images and pattern recognition to classify molars and premolars. Since then, **deep learning** has improved accuracy and popularity in this field.
- **Summary of Related Work on Teeth Classification and Numbering (2017–2021)**
  - **2017**
    - **Miki et al.**
      - Model: **AlexNet**
      - Data: **52 CBCT images**
      - Task: Classify **7 types of teeth**
      - Accuracy: **91%**
    - **Oktay et al.**
      - Model: **AlexNet**
      - Data: **100 DPR images**

    - Task: Classify **3 types of teeth**
    - Accuracy: **>90%**
- ## 2018
  - **Zhang et al.**
    - Model: **VGG16**
    - Data: **1000 X-ray images**
    - Task: Recognize and number **32 teeth**
    - Precision/Recall: **>95%**
  - **Tuzoff et al.**
    - Model: **VGG16**
    - Data: **1574 DPR images**
    - Task: Teeth detection and numbering
    - Sensitivity/Precision: **>99%**
    - Numbering accuracy: **>98%**
- ## 2019
  - **Chen et al.**
    - Model: **ResNet**
    - Data: **1250 periapical images**
    - Task: Tooth detection and numbering
  - **Muramatsu et al.**
    - Models: **DetectNet, GoogLeNet, ResNet**
    - Data: **100 DPR images**
    - Sensitivity: **96%**
    - Accuracy: **>93%**
- ## 2020
  - **Sukegawa et al.**
    - Models: **VGG-16, VGG-19**
    - Data: **8859 X-ray images** (implants)
    - Task: Classify **11 implant types**
    - Accuracy: **>90%**
  - **Kim et al.**
    - Model: **R-CNN + heuristics**
    - Data: **303 DPR images**
    - Tooth recognition: **>96%**
    - Tooth numbering: **>84%**
  - **Yasa et al.**

        - Model: **Faster R-CNN + Inception v2**
        - Data: **1125 bitewing radiographs**
        - Sensitivity: **97.48%**
        - Precision: **92.93%**
        - F1-score: **95.15**
  - ## 2021
    - **Kılıç et al.**
      - Model: **Faster R-CNN + Inception v2**
      - Data: **421 DPR images (children)**
      - Task: Deciduous teeth detection and numbering
      - Performance:
        - **F1-score:** 96%
        - **Precision:** 95%
        - **Sensitivity:** 98%
  - ## General Insights:
    - CNNs like **AlexNet**, **VGG16/19**, **ResNet**, and **Inception-based Faster R-CNN** dominate dental image classification tasks.
    - Most studies use **X-ray images** (DPR, CBCT).
    - Excellent performance is achievable even with modest dataset sizes
    - Recent trends include **region-based CNNs** and **heuristic-aided models** for better accuracy.
- **Related Work**
  - ## Tooth Recognition and Numbering
    - **Görürgöz et al.**
      - Model: **GoogLeNet**
      - Data: **1,686 X-ray images**
      - Performance:
        - **F1-score:** 87%
        - **Precision:** 78%
        - **Sensitivity:** 98%
    - **Estai et al.**
      - Model: **VGG-16**
      - Data: **591 DPR images**
      - Achieved:
        - **Tooth detection:** Recall & Precision **>99%**
        - **Tooth numbering: >98%**

- ## Tooth Disease Detection (Emerging Focus)
  - **Prajapati et al.**
    - Task: Disease classification on **251 DPR images**
    - Model: **VGG-16**
    - Accuracy: **>88%**
  - **You et al. (2020)**
    - Task: **Calculus area detection** from intraoral RGB images
    - Method: Manual cropping, trained model on disclosing-agent tooth images
    - Result:
      - **Mean IoU (MIoU):**
        - AI model: **0.724 ± 0.159**
        - Human expert: **0.652 ± 0.195**
- ## Insight:
  - Most prior work focused on **tooth detection and numbering using X-rays**.
  - Recent studies are now exploring **disease detection using color images**.
  - Deep learning shows promise even **in outperforming human experts** in some dental diagnostics.

- **Motivation & Contribution of the Paper**
  - ## Problem & Gap in Literature
    - Most existing research uses **X-ray images** for dental disease detection.
    - There are **few studies** that use **RGB (color) images** for detecting tooth diseases.
    - Previous work (e.g., by **Li et al.** and **You et al.**) showed color images can detect **plaque**, but datasets were limited and methods not widespread.
  - ## Challenges
    - **Labeled color image datasets** for dental diseases are **rare and small**.
    - Deep learning models usually need **large datasets**, which makes training on small color image datasets difficult.
  - ## Paper’s Contribution
    - Proposes a **deep learning model** to detect **periodontal diseases** (like **calculus** and **inflammation**) using **color tooth images**.
    - **Data source:** Images taken **in front of the mouth** using **optical cameras**, collected from the **internet**.
    - The method:
      - Automatically **detects the tooth region**.
      - **Classifies** the image as **diseased or healthy**.

- Introduces a **novel CNN architecture** using:
  - **1D convolutions** in parallel.
  - **Shortcut connections** to enhance training on small datasets.

2. Methods

2.1. Data Acquisition

- **Dataset Overview**
  - **Total Images**: 220 frontal tooth images collected from the **internet**.
    - **82 healthy teeth**
    - **138 teeth** with **calculus** or **inflammation** (i.e. periodontal diseases)
- **Labeling Process**
  - All images captured **with a mouth opener** to ensure full visibility of teeth.
  - **Manual classification** was done by:
    - Two **dental hygiene experts**
    - One **dentist**
  - Labeled images are publicly available at:
    🔗 https://github.com/PKNU-PR-ML-Lab/calculus
- **Annotation Details**
  - **Bounding boxes** were created to label tooth areas.
  - Used the open-source tool **Roboflow**
    🔗 https://roboflow.com
  - **Manual labeling** ensured accuracy.
- **Preprocessing**
  - All images were **resized to (640, 640, 3)** to standardize input for the neural network.
  - Images kept their **aspect ratio**, and empty areas were **zero-padded**.
  - **Pixel values normalized** to a range between **0 and 1**

2.2. Method Overview

- **Objective**
  The proposed system performs **periodontal disease recognition** using two main steps:
  1. **Teeth Region Detection**
  2. **Classification of Teeth** (with or without **calculus/inflammation**)
- **Why Teeth Detection?**
  - Isolating the **teeth area** boosts **accuracy** and helps **avoid overfitting**, especially when working with a **small dataset**.
- **Validation Strategy**

- Used **10-fold cross-validation** for reliable performance assessment:
  - **90%** of data used for **training**
  - **10%** used for **testing**
- This process was **repeated 10 times**, each with different splits.
- The **same data split** was consistently applied for both the **detection** and **classification** phases.

2.3. Tooth Region Detection

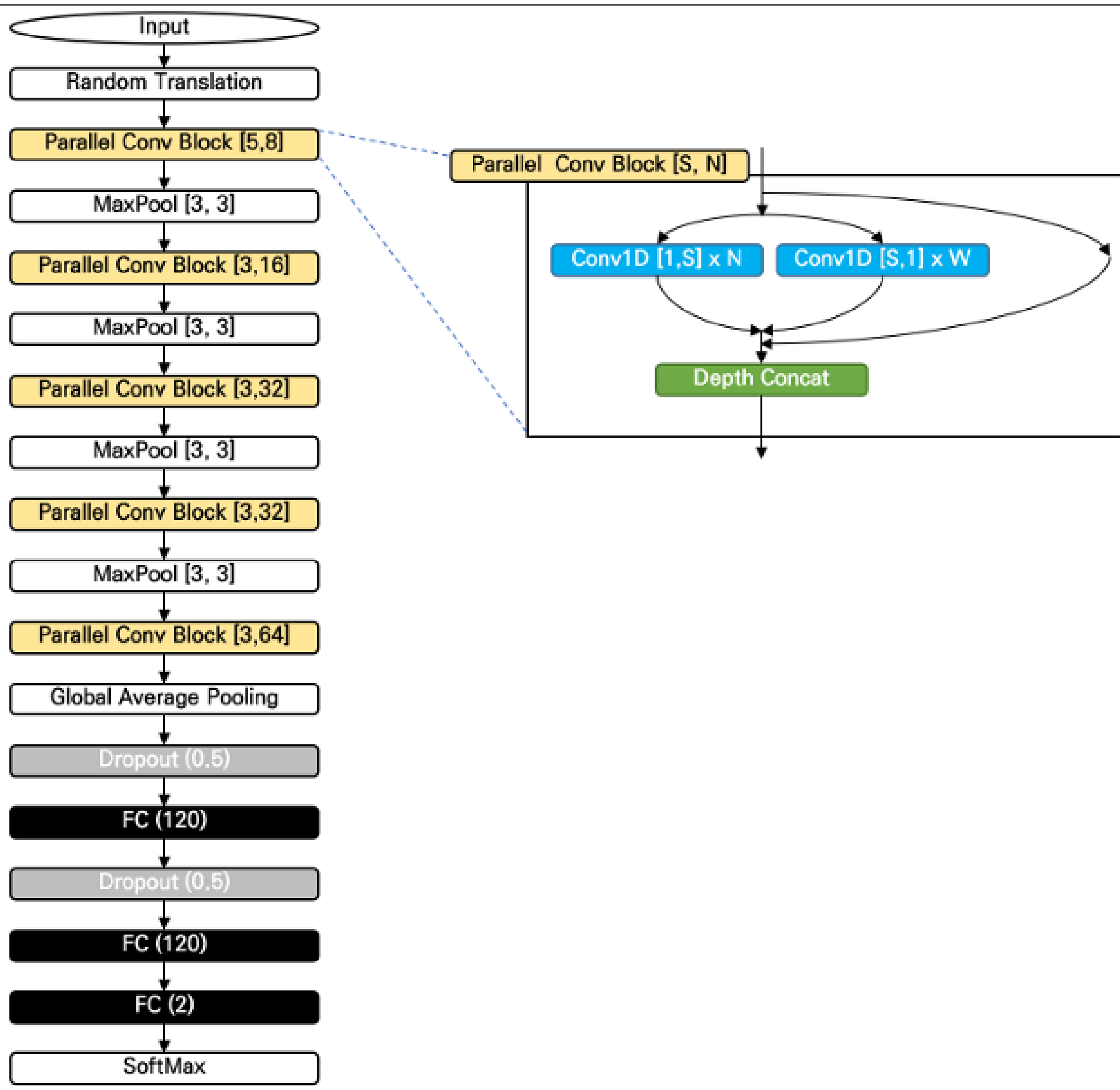
- **Tool Used**
  - **YOLOv5 (You Only Look Once v5)** was used for detecting the **tooth region**.
  - Developed by **Ultralytics** in 2020.
  - Known for being **faster and more accurate** than earlier YOLO versions.
- **Model Configuration**
  - **YOLOv5s** variant (the small version) was chosen:
    - ✅ Best for simple tasks (like detecting just one object: the tooth).
  - **Training settings**:
    - **Epochs**: 300
    - **Batch size**: 8
    - **Transfer learning** was applied using **pretrained weights**.
    - Optimizer: **SGD** (Stochastic Gradient Descent)
      - Includes **momentum**, **learning rate**, and **decay** adjustments.

2.4. Calculus Classification

- **Network Design Overview**
  - The proposed deep learning model aims to classify **periodontal disease (calculus & inflammation)** using **RGB optical images**.
  - The model processes input through several stages:
    - **Parallel Conv Blocks** with 1D convolutions (horizontal & vertical filters).
    - **MaxPooling layers** for spatial downsampling.
    - **Global Average Pooling** to flatten spatial features.
    - **Dropout** layers (0.5) for regularization.
    - **Fully Connected (FC)** layers, ending with **Softmax** for binary classification (healthy vs diseased).
- **Parallel Conv Block**
  - Introduces **two parallel 1D convolutions**:
    - One for detecting **horizontal features**: `Conv1D[1, S]`

- One for **vertical features**: `Conv1D[S, 1]`
- Combines their outputs via **Depth Concatenation**.
- Designed to be **lightweight**, using **2/3 fewer weights** than standard 2D convolutions.

- **Shortcut Connections**
  - Inspired by **ResNet**, shortcut paths are added inside the blocks.
  - Helps **deepen the network** without degrading performance.
  - Improves training stability and gradient flow.
- **Alternative Block Structures**



- **Figure 5.** Proposed network structure for calculus and inflammation classifications.

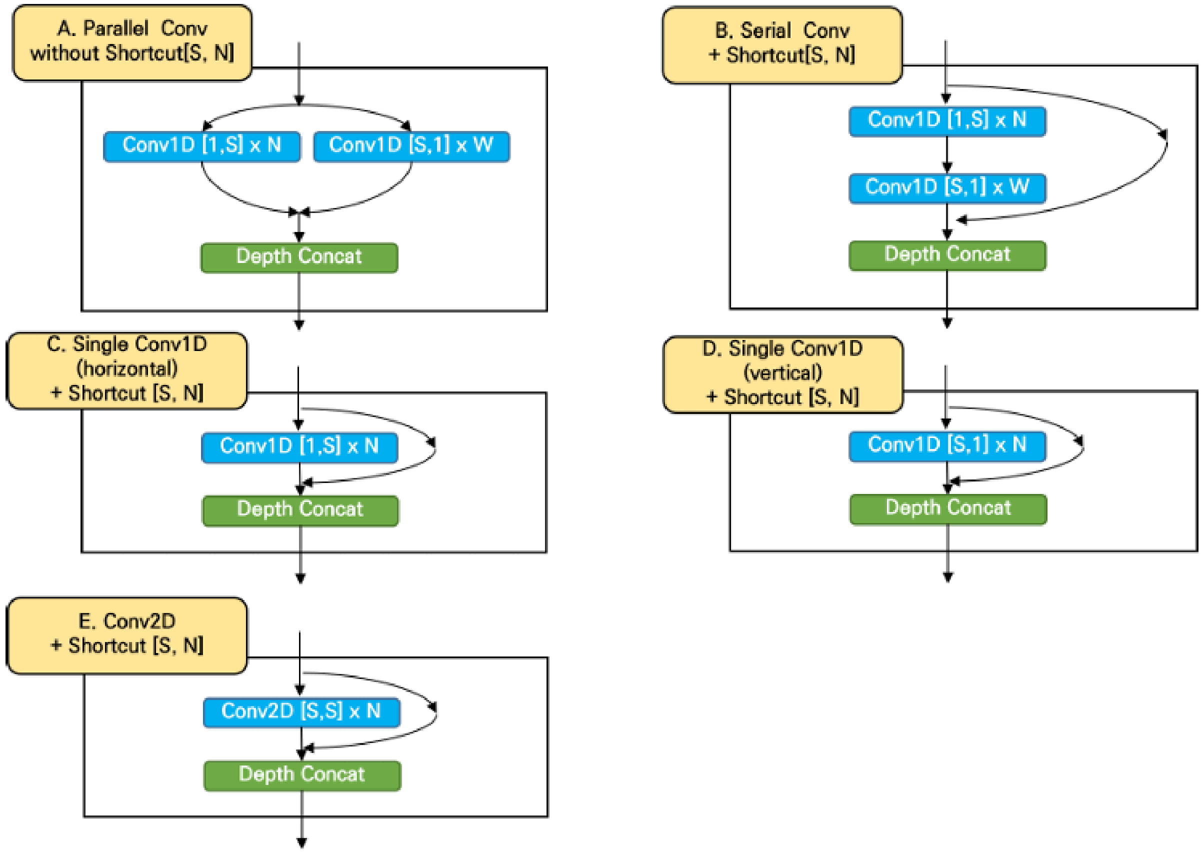


Figure 6. Five different types of convolutional blocks.

- The study compared 5 architectural variants:
  1. **A. Parallel Conv without Shortcut** – Just the two Conv1D paths.
  2. **B. Serial Conv + Shortcut** – Conv1Ds applied in series, not in parallel.
  3. **C. Single Conv1D (Horizontal) + Shortcut**
  4. **D. Single Conv1D (Vertical) + Shortcut**
  5. **E. Standard Conv2D + Shortcut**
- *Finding:* The **parallel structure with shortcuts** (used in the proposed model) balances **high performance** and **low parameter count**, outperforming traditional Conv2D in small datasets.

3. Results

3.1. Tooth Detection

- **Key Insights:**
  - While **tooth detection using radiographic images** (like CBCT, panoramic, and periapical X-rays) is well-studied with high accuracy using CNN-based models (like AlexNet, VGG, and Inception), **few studies** have used **RGB color images** for tooth detection.

- In this study, the authors applied **YOLOv5s** for detecting the **entire tooth region** from **RGB frontal mouth images**.
- This task is simpler than detecting individual teeth, which led to **very high detection performance**:
  - **F1 Score**: **99.99%**
  - **mAP@50**: **99.5%**
- Tooth Detection Studies Summary

Year	Image Type	Goal	Dataset Size	Model	Accuracy / Metric
2017	CBCT	Tooth classification (7 cls)	52	AlexNet	88.4% (Accuracy)
2017	Panoramic	Tooth detection (3 cls)	100	AlexNet	92.84% (Accuracy)
2018	Periapical	Tooth classification (binary)	1000	VGG16	98.1% (F1 Score)
2019	Periapical	Tooth classification (binary)	1250	ResNet	98.65% (F1 Score)
2018	Panoramic	Tooth detection	1574	VGG16	99.42% (F1 Score)
2020	Panoramic	Tooth detection	303	InceptionV3	96.7% (mAP)
2020	Bitewing	Tooth classification (12 cls)	1125	InceptionV2	95.15% (F1 Score)
2021	Panoramic	Tooth detection	421	InceptionV2	96.86% (F1 Score)
2023 This paper	**Color (RGB)**	**Teeth region detection**	**220**	**YOLOv5s**	**99.99% (F1 Score)**

3.2. Classification of Periodontal Disease

- **Performance of the Proposed Model:**
  - The **proposed Parallel 1D CNN with shortcut connections** achieved a **classification accuracy of 74.54%**, significantly outperforming the baseline **ResNet152 model**, which achieved **63.09%**.
  - When **shortcuts were removed**, accuracy dropped by **7.72%**, proving their effectiveness.
  - Other tested architectures showed lower accuracy:
    - **Single 1D (vertical)** + shortcut: **69.54%**

- **Single 1D (horizontal)** + shortcut: **68.19%**
    - **Serial 1D convolution**: **67.73%**
    - **2D convolution**: **65.00%**
- **Key Result:**
    - The **proposed network outperformed ResNet152 by 11.45%**, demonstrating its ability to **learn well even with a small dataset**.
- **Comparison with Related Works**

Year	Data Type	Dataset Size	Target Disease(s)	Model	Accuracy / AUC / mIoU
2021	RGB Images	921	Calculus, Gingivitis, Deposits	Multi-task CNN	AUC: 80.11 (calculus)
2020	RGB Images	607	Plaque	Super-pixel CNN	Accuracy: 86.42%
2020	Intraoral RGB Images	886	Plaque	CNN	mIoU: 0.726
2020	Panoramic X-ray Images	65	Plaque	Faster R-CNN	AUC: 83
2023 **This Paper**	Optical Color Images	220	**Calculus, Inflammation**	**Parallel 1D CNN**	**Accuracy: 74.54%**

4. Conclusion

- **Importance**: Analyzing **teeth using color images** is crucial for assessing oral health in a more accessible way, especially for everyday users.
- **Problem Gap**: While many studies focus on X-ray images, **color image-based tooth analysis** is still underexplored.
- **Contribution**: This paper proposed a **CNN model using one-dimensional parallel convolutions** and **shortcut connections** to classify **periodontal diseases (calculus & inflammation)** using **frontal color images**.
- **Model Strength**:
    - Achieved **11.45% higher accuracy** than ResNet152.
    - Effective even with a **small dataset**, helping reduce **overfitting**.
- **Impact**: Shows strong potential for **mobile oral healthcare applications**, using regular smartphone cameras instead of specialized equipment.
- **Future Work**:
    - Train on **larger and more diverse datasets**.

- Include **teeth images without a mouth opener** for better real-world applicability.
- Further explore the **use of 1D parallel convolution structures** in other image classification tasks.

Resources :

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Related notes :

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References :

- **Internal :**
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- **External :**
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