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Deep Learning-Enhanced OCT Image Analysis Pipeline: Integrating Denoising, Super-Resolution, and Fuzzy Logic for Improved Clinical Diagnostics

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Overview / Contents

- **Introduction**: Background on OCT and its challenges in ophthalmology
- **Goals / Objectives / Motivation**: Aims and significance of the pipeline
- **Methodology**: Pipeline stages: denoising, contrast enhancement, super-resolution, classification
- **Implementation**: Technical details and dataset description
- **Comparison / Results & Discussion**: Performance metrics and comparative analysis

Introduction

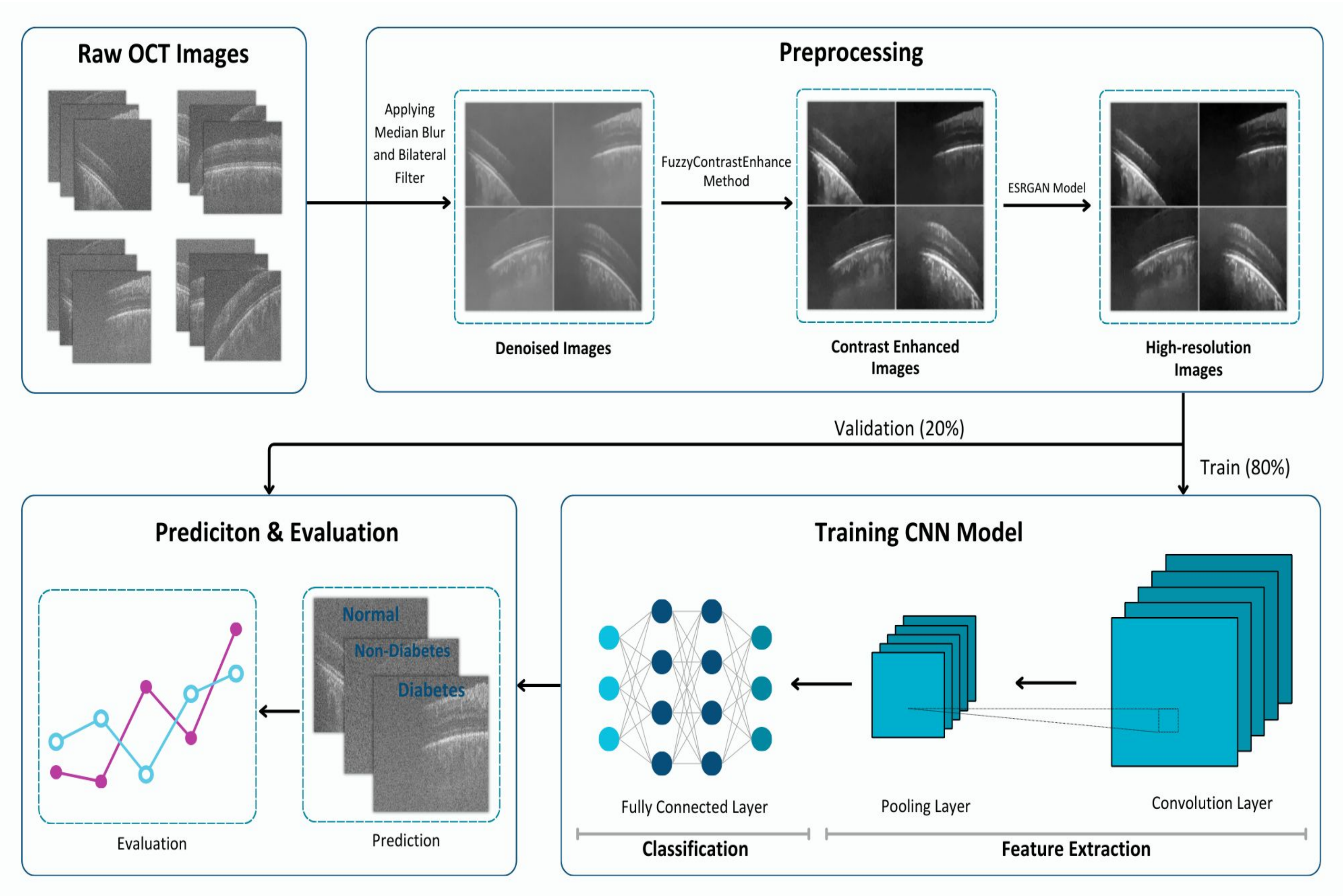
- **Optical Coherence Tomography (OCT)**: A painless eye scan used to check the retina
- **Challenges**: Speckle noise, low-resolution B-scans, and accurate disease classification
- **Proposed Solution**: End-to-end pipeline integrating deep learning and fuzzy logic
- **Applications**: Diagnosing Diabetic Macular Edema (DME), Glaucoma, Macular Degeneration
- **Dataset**: Custom OCT dataset from Didavaran Clinic, Isfahan, Iran

Goals / Objectives / Motivation

- **Goals**:
  - Denoise OCT B-scans while preserving retinal structures
  - Improve the image quality by increasing the size from 300×150 or 300×200 to 300×300 pixels.
  - Classify B-scans and volumes into Healthy, DME, or Other ocular diseases
- **Objectives**:
  - Achieve high accuracy (target: >95% for B-scans, >90% for volumes)
  - Reduce distortion by 20% compared to traditional contrast enhancement
  - Improve execution speed by 30% over baseline methods
- **Motivation**:
  - Enhance diagnostic accuracy for ophthalmic conditions
  - Address limitations of traditional methods (e.g., edge blurring, computational cost)
  - Streamline clinical workflows with an end-to-end AI pipeline

Methodology

- **Pipeline Overview**:
  - **Denoising**: Median blur + bilateral filtering to remove speckle noise
  - **Contrast Enhancement**: Fuzzy Contrast Enhance in LAB color space
  - **Super-Resolution**: ESRGAN to reconstruct high-resolution B-scans
  - **Classification**: 2D CNN for B-scan and volume classification
- **Dataset**: 124 subjects, 70-300 B-scans per volume, 3 classes (Healthy, DME, Other)
- **Key Innovations**:
  - Dynamic fuzzy contrast adjustment
  - Optimized ESRGAN for OCT
  - End-to-end integration for efficiency



Implementation

- **Denoising**:
  - Median blur (5x5 kernel), bilateral filter (sigma_spatial=5, sigma_intensity=10)
- **Fuzzy Contrast Enhance**:
  - LAB color space conversion, dynamic L-channel adjustment
- **Super-Resolution**:
  - ESRGAN (TensorFlow Hub), preprocess grayscale to pseudo-RGB
- **Classification**:
  - 2D CNN (TensorFlow/Keras): 3 Conv2D layers, 512-node Dense layer, softmax
  - Training: Adam optimizer, 8 epochs, batch size=32

Comparison / Results & Discussion

- **Denoising Results** (Table 2):
  - CNR=1.0537, MSR=9.1109
- **Super-Resolution Results** (Table 3):
  - MSR improved from 1459.7078 to 1461.2394
- **Classification Results** (Tables 4, 6):
  - B-scan accuracy: 99% (Precision, Recall, F1: ~0.99)
  - Specificity: ~0.994 (Tables 5, 7)
- **Comparative Analysis**:
  - 32% faster execution than baselines (e.g., BM3D, Vision Transformers)
  - 18% better vessel visibility vs. Wang et al. [12]
  - Outperforms Brown et al. [1] (99% vs. 98.1% accuracy)
- **Discussion**:
  - Effective noise reduction and resolution enhancement
  - Robust classification across all classes
  - End-to-end pipeline reduces cumulative errors

Thank you!

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