Enhancing the Detection of Alzheimer's Disease Using Magnetic Resonance Imaging Data through Convolutional Neural Networks

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ABSTRACT

- **Problem**: Alzheimer's disease (AD) is a global health issue requiring precise diagnostic tools for early intervention.
- **Method:** This study utilizes convolutional neural networks (CNNs) and MRI data to improve AD detection accuracy.
- **Key Results:** The YOLO8 model achieved 98% accuracy, significantly outperforming traditional methods.
- **Impact:** These findings provide a foundation for scalable diagnostic tools to integrate into clinical workflows.

INTRODUCTION

- Alzheimer's disease (AD) causes progressive cognitive decline, impacting millions globally. Early diagnosis is critical for effective treatment but is limited by current methods.
- MRI captures brain changes linked to AD before symptoms fully develop.
- Leverage CNNs, a deep learning technique effective in image classification, to enhance AD detection precision.
- This research addresses limitations in traditional methods by optimizing CNNs for MRI-based diagnosis.

AIMS

- Evaluate CNN performance in classifying AD from MRI scans.
- Optimize machine learning techniques to improve diagnostic precision and address overfitting challenges.

RESULTS

Model	Accuracy	Precision	Recall	F1
YOLO11-cis	83%	88%	79%	83%
YOLO8-cis	82%	90%	77%	83%
YOLOv5	79%	86%	90%	90%
Random Forest	73%	73%	73%	72%
Logistic Regression	66%	68%	66%	65%
SVM	67%	69%	67%	67%
DenseNet121	52%	25%	50%	33%
ResNet50	50%	25%	50%	33%
VGG16	50%	25%	50%	33%
VGG19	50%	25%	50%	33%
EfficientNetB0	50%	25%	50%	33%
InceptionV3	50%	25%	50%	33%
ResNet101	49%	37%	50%	33%

Table 1: Model Performance Metrics: A table summarizing the performance of various machine learning and deep learning models across four metrics: accuracy, precision, recall, and F1-score.

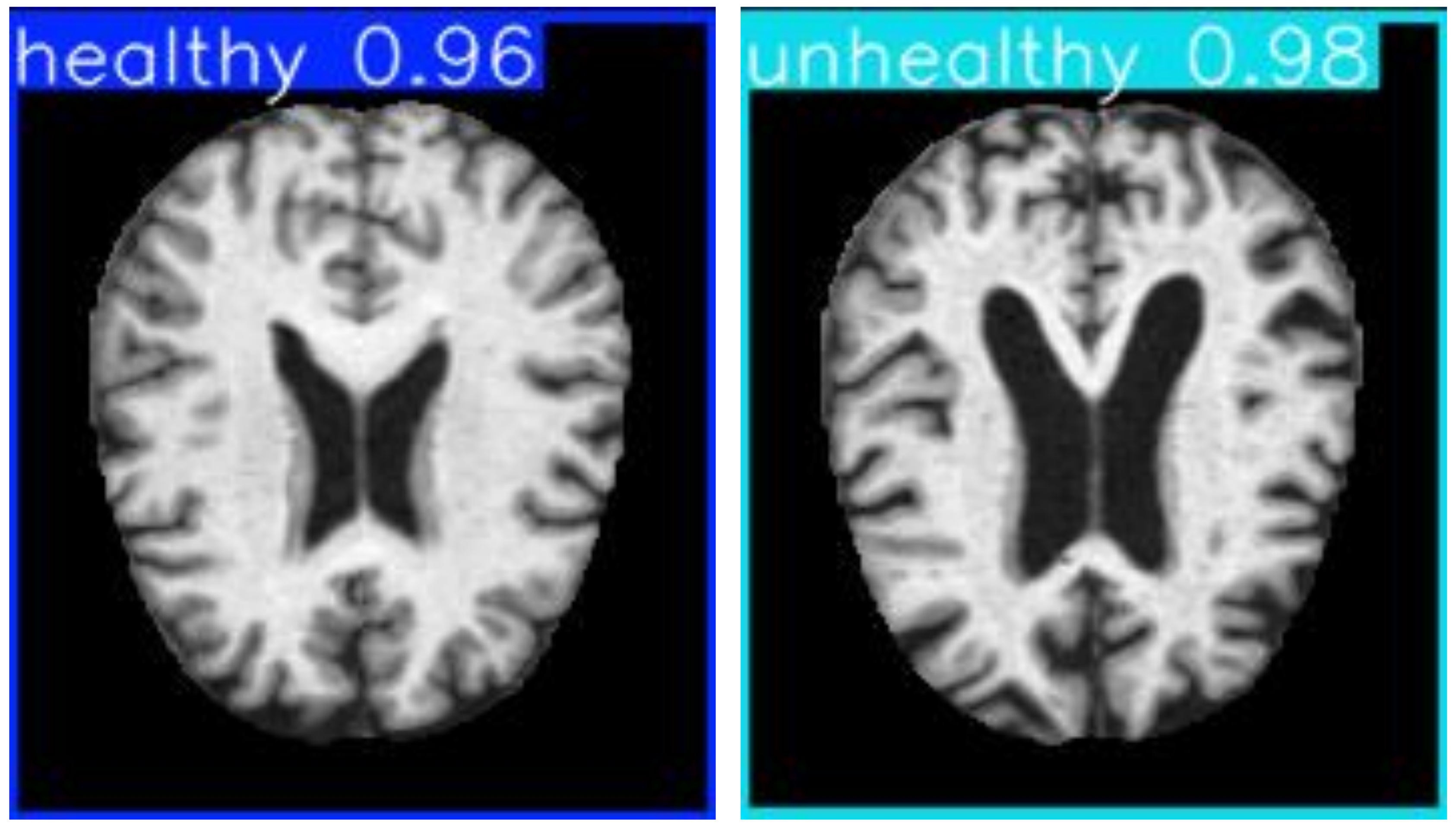

Figure 2: MRI Classification Examples: This figure shows two MRI images classified by the YOLO5 model. The image on the left is classified as "Healthy" with a confidence score of 0.96, while the image on the right is classified as "Unhealthy" with a confidence score of 0.98.

- YOLO11-cis: Highest accuracy (83%) with strong precision (88%) and balanced recall (79%).
- Random Forest: Best traditional model with 73% accuracy and balanced precision/recall.
- Confidence scores (e.g., 0.96 for "healthy" and 0.98 for "unhealthy") reflect YOLO's reliability for individual predictions.

METHODS

- Training Set Image Counts:
  - Healthy (Non-Demented): 2560 images
  - Unhealthy (Very Mild, Mild, Moderate Demented): 2562 images
- Test Set Image Counts:
  - Healthy (Non-Demented):634 images
  - Unhealthy (Very Mild, Mild, Moderate Demented): 640 images

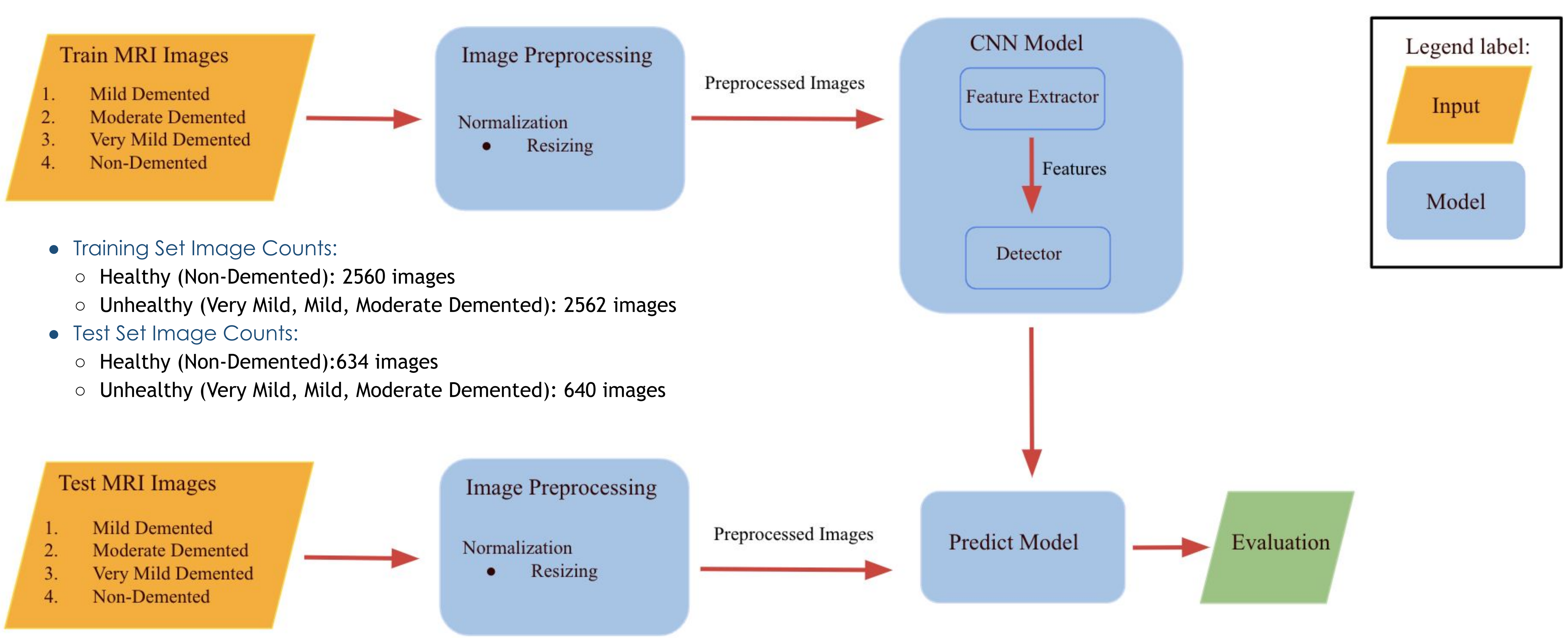

Figure 1: CNN Pipeline for MRI Classification: A flowchart outlining the end-to-end process of MRI image classification. Input: MRI images categorized into four classes (Mild Demented, Moderate Demented, Very Mild Demented, and Non-Demented). Preprocessing: Images undergo normalization and resizing to ensure compatibility with the CNN model. CNN Model: Features are extracted and classified into "Healthy" or "Unhealthy." Output: Predicted classifications are evaluated based on accuracy and other metrics.

FUTURE WORK

- Model interpretability: Use SHapley Additive exPlanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME) for better clinical trust and transparency.
- Dataset improvement: Use data augmentation techniques and expand datasets to address class imbalance.
- Model optimization: Experiment with fine-tuned hyperparameters and employ transfer learning to improve performance.
- Operational integration: Collaborate with healthcare professionals for real-world testing and clinical adoption.

CONCLUSIONS

- Summary of Impact:
  - CNNs, especially YOLO models outperform traditional methods and other deep learning architectures, excelling in both precision and recall, making them robust for classification tasks.
- Broader Implications:
  - Findings highlight the feasibility of integrating deep learning into diagnostic workflows.
- Next Steps:
  - Extend this research to larger datasets and evaluate performance across diverse populations.