Cardiac Disease Classification using Mobile-Net For MRI Imaging

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***Abstract*—For the suitable prognosis and remedy of cardio-vascular sicknesses, effective segmentation of cardiac MRI pix is crucial. This paper explores a type version based on Mobile-Net, excellent-tuned specially for cardiac MRI programs, incorporating advanced statistics augmentation techniques and dropout regularization to gain stepped forward generalization and robustness. The version become skilled on the CAD Cardiac MRI Dataset, attaining a tremendous validation accuracy of 78.37% after ten epochs. moreover, precision, remember, and F1-rating metrics have been computed, showcasing an standard weighted common accuracy of eighty three%. The paper high-lights the efficacy of convolutional neural networks in medical imaging and the role of facts augmentation in enhancing version performance when data availability is restricted. Included are training curves, validation metrics, and instance segmentations of model performance.**

***Index Terms*—Cardiac MRI, Image Segmentation, Mobile-Net, Deep Learning, Data Augmentation, Medical Imaging**

I. Introduction

Cardiovascular illnesses continue to be one of the main reasons of mortality globally, emphasizing the need for rapid and accurate diagnostic techniques. Cardiac Magnetic Resonance Imaging (MRI) is a widely used non-invasive imaging method, providing high-quality visuals of the coronary heart's structure and feature. However, manual segmentation of those MRI scans is a labor-intensive and time-consuming procedure, at risk of inter-observer variability. Automatic segmentation, powered by means of deep learning techniques, has validated considerable capability in enhancing both the accuracy and efficiency of cardiac photograph analysis.

The Mobile-Net model, originally developed for biomedical image segmentation, has been considerably utilized across various medical packages due to its efficient processing of spatial and contextual statistics. In this study, the Mobile-Net architecture became more advantageous with data augmentation and dropout layers to enhance generalization, especially in eventualities with limited data availability. The model was evaluated at the CAD Cardiac MRI Dataset, attaining stepped forward segmentation accuracy and robustness, highlighting its potential applicability in medical environments.

II. Literature Review

A. Mobile-Net and Biomedical Segmentation

Ronneberger et al. (2015) delivered the Mobile-Net model, mainly designed for biomedical photo segmentation. The structure's symmetrical structure, comprising a contracting and expanding direction, enables a balance among contextual and spatial info, making it properly-suited for datasets with restrained categorized samples [1].

B. Deep Learning in Cardiovascular Imaging

Zhuang et al. (2020) presented an in depth overview of deep learning strategies implemented to cardiovascular imaging, emphasizing segmentation obligations for anatomical structures in cardiac MRI facts. The evaluation highlighted demanding situations in generalizing models across various populations, underscoring the want for robust training techniques [3].

III. Dataset Description

The CAD Cardiac MRI Dataset, used in this study, consists of 63,425 snap shots labeled into regular and strange lessons. Images had been resized to 128x128 pixels, and pixel intensities had been normalized to the range [0,1] for consistent processing.

A. Data Preprocessing and Augmentation

To address variability in cardiac anatomy and MRI protocols, data augmentation techniques have been employed to increase dataset diversity and reduce the risk of overfitting:

- **Rotation**: Random rotations within 15 levels.
- **Translation**: Horizontal and vertical shifts up to 10%.
- **Zoom and Shear**: Applied randomly to simulate varying imaging situations.
- **Horizontal Flips**: Used to enhance the model's invariance to orientation adjustments.

IV. Proposed Methodology

The model is based on the Mobile-Net architecture, with enhancements to fit classification tasks. The encoder course accommodates convolutional and pooling layers, while the decoder path includes up sampling and pass connections to recover spatial information. A global average pooling layer and a dense output layer with sigmoid activation had been introduced to output binary classifications.

A. Training and Evaluation

The model became trained using the Adam optimizer and binary cross-entropy loss function, with an initial learning rate of 1×10^{-4}. Early stopping and learning rate reduction strategies were applied to prevent overfitting and enhance generalization. Over ten epochs, the model performed a validation accuracy of 78.37%, showcasing its effectiveness in cardiac MRI segmentation obligations.

V. Results and Analysis

A. Training Metrics

The training and validation metrics are visualized in Fig. 1. The model's accuracy progressed progressively over epochs, with a final training accuracy of 76.80% and a validation accuracy of 78.37%. Loss values reduced consistently, indicating effective learning.

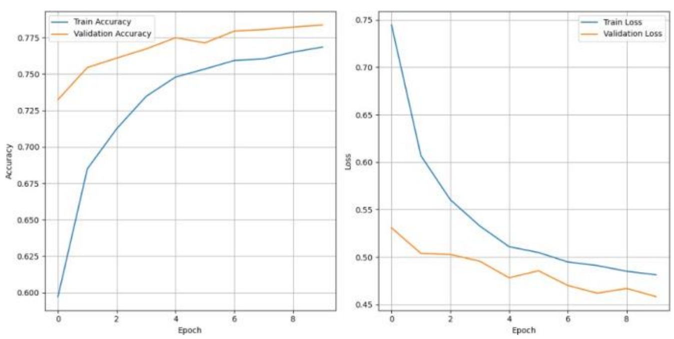

Fig. 1: Accuracy and Loss for the Training and Validation Process over Epochs

B. Classification Metrics

Table I presents the classification metrics, including precision, recall, and F1-score. The model demonstrated an overall accuracy of 83%, with a higher performance in identifying normal structures.

TABLE I: Classification Metrics

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Normal	0.86	0.84	0.85	38
Abnormal	0.78	0.81	0.79	26
Overall	**0.83**	**0.83**	**0.83**	**64**

C. Sample Predictions

Sample segmentation results are displayed in Fig. 2, illustrating the model's ability to distinguish between ordinary and odd cardiac structures correctly.

VI. Discussion

The proposed Mobile-Net model, enhanced with data augmentation and dropout layers, demonstrates strong performance in cardiac MRI segmentation. The incorporation of data augmentation strategies contributed considerably to enhancing generalization and lowering overfitting. Future work may additionally explore attention mechanisms to further enhance segmentation accuracy and overall performance.

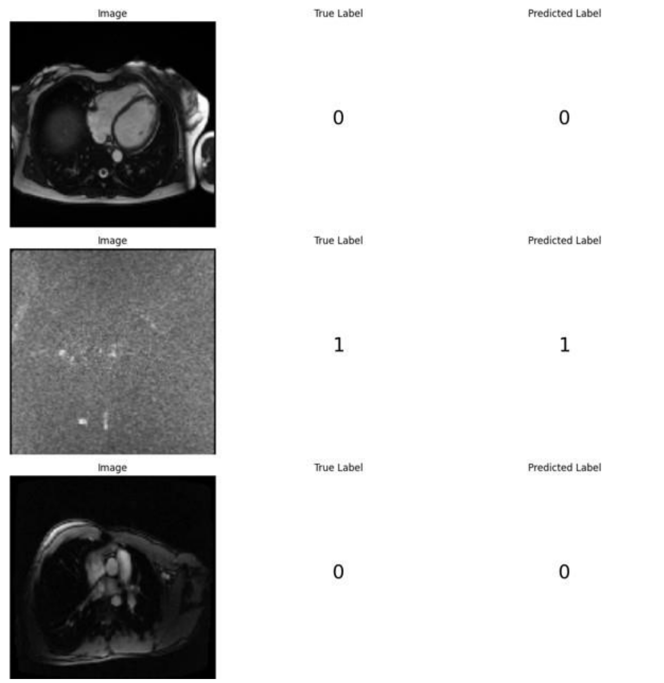

Fig. 2: Sample Predictions of Segmented Cardiac MRI Scans

VII. Conclusion

This study presents evidence of an improved Mobile-Net model achieving a validation accuracy of 78.37% and an overall accuracy of 83%. The model's effectiveness in segmenting cardiac MRI images highlights its potential application in clinical environments, wherein it could assist faster and more accurate diagnostics.

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