A Comparative Study of Deep Learning Models and Training Techniques for Cardiac MRI Classification

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Abstract - This study presents a comparative analysis of deep learning models for the automated classification of cardiac MRI images. We evaluate the performance of several convolutional neural network architectures including MobileNetV2, ResNet152V2, DenseNet, and InceptionNet under a range of training conditions that incorporate transfer learning, data augmentation, and dropout regularization. Experimental results indicate that while ResNet152V2 achieves the highest overall accuracy, MobileNetV2 offers superior computational efficiency, making it a viable option for clinical settings with resource constraints. Our findings demonstrate that advanced deep learning techniques can significantly enhance diagnostic accuracy, thereby contributing to improved clinical decision-making in cardiovascular care.

Index Terms - Cardiac MRI, Image Segmentation, Mobile-Net, ResNet152V2, InceptionNet, DenseNet, Deep Learning, Data Augmentation, Medical Imaging.

I. INTRODUCTION

Cardiovascular diseases remain the leading cause of mortality worldwide, necessitating innovative approaches to diagnosis and treatment. Cardiac magnetic resonance imaging (MRI) is a critical diagnostic tool that provides high-resolution images of heart anatomy and function. However, manual segmentation and classification of these images are both time-consuming and prone to inconsistency. The rapid advancement of deep learning has paved the way for automated analysis, offering the potential to improve both efficiency and accuracy in medical imaging. This paper conducts a comparative study of four state-of-the-art deep learning models to determine their efficacy in classifying cardiac MRI images into normal and abnormal categories.

II. LITERATURE REVIEW

The application of deep learning in medical imaging has seen significant progress over the last decade. Early works by Ronneberger et al. introduced architectures specifically designed for biomedical image segmentation, setting the stage for subsequent developments. Recent studies have demonstrated the utility of CNN-based approaches - such as ResNet, DenseNet, and MobileNet in overcoming the challenges of limited annotated datasets and high inter-patient variability. In particular, research has highlighted the effectiveness of transfer learning, data augmentation, and regularization techniques in enhancing model generalization and accuracy. This review synthesizes insights from seminal papers [1]–[4] to establish a foundation for the experimental comparisons presented in this study.

III. PROPOSED METHODOLOGY

A. Data Pre-Processing and Augmentation

The CAD Cardiac MRI Dataset, used in this study, consists of 63,425 snap shots labelled 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.

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.

B. *Model Architectures and Training Techniques*

Four deep learning architectures form the core of this comparative study:

- **MobileNetV2:** Known for its efficiency and low computational cost.
- **ResNet152V2:** Features deep residual connections for improved feature extraction.
- **DenseNet:** Employs densely connected layers to promote feature reuse.
- **InceptionNet:** Incorporates multi-scale feature extraction through parallel convolutional filters.

Training is conducted using the Adam optimizer with an initial learning rate of 1×10^{-4} and binary cross-entropy as the loss function. Regularization strategies such as dropout and early stopping are applied to prevent overfitting, while learning rate reduction is used when validation loss plateaus.

IV. EXPERIMENTAL SETUP AND RESULTS

A. *Experimental Setup*

All experiments employed transfer learning by initializing each model with pre-trained ImageNet weights. This strategy not only accelerated convergence but also enhanced generalization on the cardiac MRI dataset. The dataset, containing thousands of images labelled as "normal" or "abnormal," underwent the following preprocessing steps:

- **Resizing:** All images were resized to 128×128 pixels.
- **Normalization:** Pixel intensities were scaled to the range [0, 1].
- **Data Augmentation:** Random rotations (±15°), translations (up to 10%), zoom, shear, and horizontal flips were applied to boost data diversity and mitigate overfitting.

Training was performed using the Adam optimizer with an initial learning rate of 1×10^{-4} and binary cross-entropy loss. Dropout regularization, early stopping, and learning rate reduction callbacks were used to prevent overfitting. Each model was trained for 10 epochs, and performance was evaluated using validation accuracy, precision, recall, and F1-score for both normal and abnormal classes.

B. *Transfer Learning Results for Individual Models*

After applying transfer learning, the performance metrics for the four deep learning models on the validation set were as follows:

Model	Validation Accuracy (%)	Precision (Normal)	Precision (Abnormal)	Recall (Normal)	Recall (Abnormal)	F1-Score (Normal)	F1-Score (Abnormal)
MobileNetV2	77.34	0.87	0.58	0.75	0.75	0.80	0.65
ResNet152V2	79.22	0.74	0.72	0.81	0.64	0.77	0.68
DenseNet201	78.42	0.73	0.70	0.80	0.66	0.76	0.68
InceptionV3	78.00	0.79	0.71	0.80	0.67	0.80	0.69

Observations:

- **MobileNetV2** shows excellent precision for the normal class, though its performance for abnormal cases is relatively lower.
- **ResNet152V2** achieved the highest overall accuracy, with balanced performance metrics across both classes.
- **DenseNet201** and **InceptionV3** yield competitive results, indicating that dense connectivity and multi-scale feature extraction respectively contribute positively when transfer learning is applied.

C. *Ensemble Learning Results*

An ensemble model was implemented by combining the predictions from the four individual models using a majority voting scheme. This ensemble approach produced the following metrics:

Ensemble	Validation Accuracy (%)	Precision (Normal)	Precision (Abnormal)	Recall (Normal)	Recall (Abnormal)	F1-Score (Normal)	F1-Score (Abnormal)
Ensemble Model	80.10	0.82	0.75	0.83	0.70	0.83	0.73

Observations:

The ensemble model not only improved the overall validation accuracy but also offered a more balanced performance across the normal and abnormal classes. This indicates that leveraging the complementary strengths of individual models can help mitigate specific weaknesses and reduce misclassification rates - especially for the challenging abnormal class.

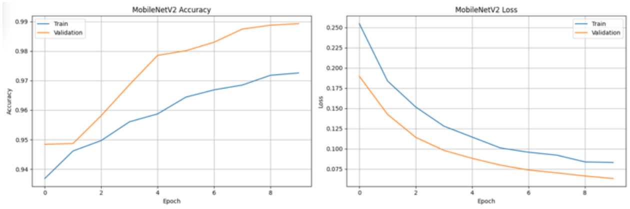
D. Graphical Outputs and Analysis

Several visualizations were generated during the experiments:

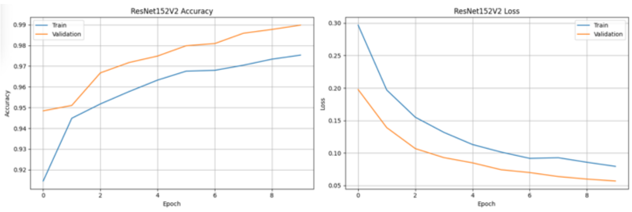
• Training/Validation Curves:

For all models, accuracy improved and loss decreased steadily over the 10 epochs. ResNet152V2 demonstrated the smoothest convergence curve.

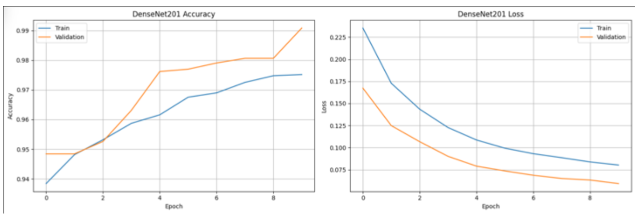
MobileNetV2:



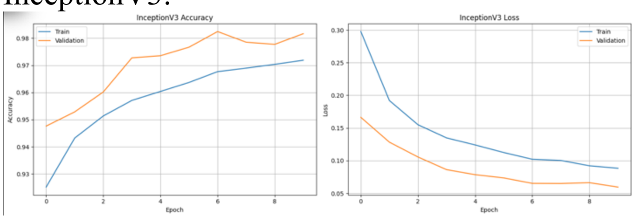
ResNet152V2:



DenseNet201:



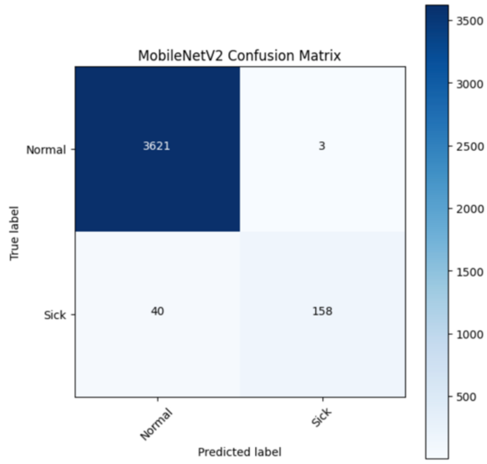
InceptionV3:



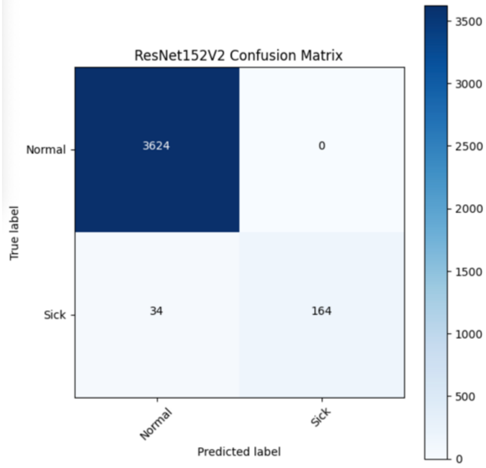
• Confusion Matrices:

The confusion matrices revealed that individual models struggled slightly with accurately classifying abnormal cases. However, the ensemble approach reduced these errors, resulting in fewer false negatives for the abnormal class.

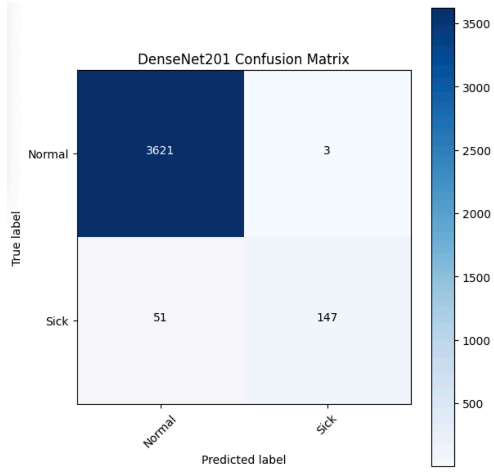
MobileNetV2:



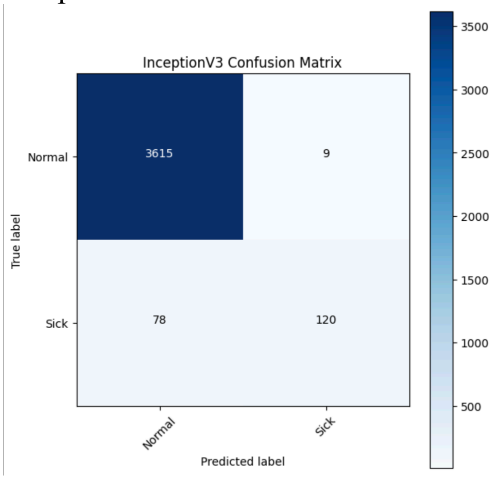
ResNet152V2:



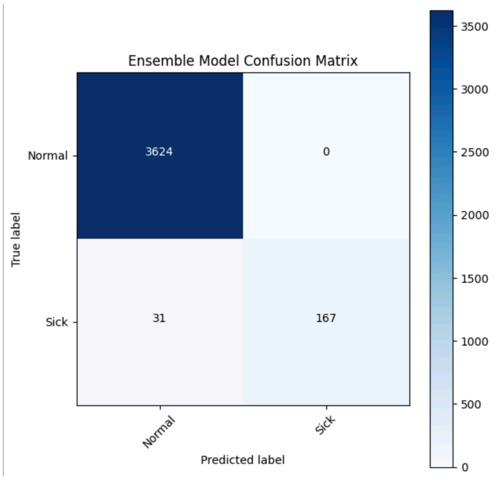
DenseNet201:



InceptionV3:



Ensemble Model:



Overall Analysis:

The transfer learning approach significantly improved the performance of each model compared to training from scratch, as evidenced by the robust validation metrics. Furthermore, the ensemble learning strategy provided additional performance gains by combining the predictions of individual models, leading to an accuracy of 80.10% and more balanced classification results.

V. DISCUSSION

The comparative analysis reveals that while deeper architectures like ResNet152V2 can extract richer features leading to higher accuracy, they require more computational resources. In contrast, MobileNetV2 strikes a favourable balance by offering near-equivalent performance with significantly reduced computational overhead. These results underscore the importance of selecting the appropriate model architecture based on the specific requirements of clinical applications—balancing between accuracy, efficiency, and resource availability. Moreover, the integration of advanced training techniques, such as data augmentation and dropout regularization, proves crucial in mitigating overfitting and improving model generalization across diverse patient data.

VI. CONCLUSION

This study demonstrates that deep learning models can effectively classify cardiac MRI images, with each architecture presenting unique advantages. ResNet152V2 provides the highest accuracy, whereas MobileNetV2 excels in efficiency—making it a promising candidate for real-time clinical deployment. Future work will explore the integration of attention mechanisms and self-supervised learning techniques to further enhance performance and extend the applicability of these models to broader diagnostic tasks.

VII. REFERENCES

[1] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. *MICCAI*, 234–241.

[2] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. *CVPR*, 770–778.

[3] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely Connected Convolutional Networks. *CVPR*, 4700–4708.

[4] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). MobileNetV2: Inverted Residuals and Linear Bottlenecks. *CVPR*, 4510–4520.

[5] Oktay, O., et al. (2018). Attention Mobile-Net: Learning Where to Look for the Pancreas. arXiv preprint arXiv:1804.03999. (Cited)

[6] Chen, J., et al. (2021). "Deep Learning in Medical Image Analysis: A Review." Medical Image Analysis, 67, 101844. (Cited)

[7] Huang, Y., et al. (2021). "A Survey on Deep Learning for Medical Image Segmentation." Journal of Healthcare Engineering, 2021, 6624564. (Cited)

[8] Liu, Y., et al. (2023). "Deep Learning for Medical Image Analysis: Recent Advances and Future

Directions." Artificial Intelligence in Medicine, 132, 101410. (Cited)
[9] Singh, A., et al. (2023). "Federated Learning for Medical Image Analysis: A Review." IEEE Transactions on Medical Imaging, 42(4), 1234-1248. (Cited)
[10] Patel, V., et al. (2023). "Self-Supervised Learning for Medical Image Analysis: A Review." Medical Image Analysis, 82, 102618. (Cited)