Deep Learning Approaches for Cardiac MRI and Heart Disease Estimation using MobileNet, Efficient Net B7, NasNet Mobile

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Abstract:

**Cardiac MRI is crucial for diagnosing heart diseases, but manual analysis is time-consuming and error-prone. This paper explores deep learning-based approaches using convolutional neural networks (CNNs) like MobileNet, EfficientNetB7, and NASNet Mobile for heart disease estimation. The models show improved accuracy, sensitivity, specificity, and inference time, making them valuable tools for medical imaging and personalized treatment plans. The deep learning models significantly outperform traditional image processing methods, offering an automated solution that can assist radiologists and clinicians in diagnosing heart conditions more quickly and accurately. The study suggests that the integration of deep learning models and cardiac MRI could revolutionize heart disease diagnostics, enhancing accessibility, reliability, and personalized patient care, emphasizing the need for further research.**

**Keywords:**

*MobileNet,EfficientNetB7,NASNET Mobile,MRI images,cardiovascular conditions imaging*

# I. Introduction

Cardiovascular diseases are a major global health concern, and early detection and accurate diagnosis are crucial for effective treatment and prevention. Cardiac Magnetic Resonance Imaging (MRI) is a non-invasive technique used to assess heart health,[(Karadeniz et al. 2021)](https://paperpile.com/c/8HuBlK/jYkJ) but interpreting images is complex and labor-intensive. As cardiac MRI data increases, there is a need for automated solutions to help healthcare professionals diagnose and monitor heart disease efficiently. [(Ye et al. 2023)](https://paperpile.com/c/8HuBlK/Lc1D)Deep learning architectures like MobileNet, EfficientNetB7, and NASNet Mobile have shown potential in medical image analysis, offering higher accuracy, faster analysis, and reduced human error. This research aims to apply these models for heart disease estimation using cardiac MRI, improving the speed, accuracy, and accessibility of heart disease diagnosis, especially in resource-constrained environments.[(Ali et al. 2023)](https://paperpile.com/c/8HuBlK/damy)

Deep learning advancements have shown potential in automating medical image analysis, particularly in cardiac MRI. CNNs can learn hierarchical features from raw data, improving classification, segmentation, and disease detection, especially in heart disease analysis. MobileNet, EfficientNetB7, and NASNet Mobile are lightweight deep learning models that offer high performance with low computational demands.[(Ieki et al. 2022)](https://paperpile.com/c/8HuBlK/ww4n) These models are particularly promising for real-time heart disease classification using cardiac MRI. MobileNet uses depthwise separable convolutions, EfficientNetB7 optimizes accuracy and computational efficiency, and NASNet Mobile finds optimal architectures for resource-constrained environments. This study compares deep learning models MobileNet, EfficientNetB7, and NASNet Mobile's performance in classification accuracy, sensitivity, specificity, and inference time for real-world clinical applications, demonstrating their potential to improve heart disease diagnostics using cardiac MRI[(Saba et al. 2021)](https://paperpile.com/c/8HuBlK/RuFn).

# II. Related Work

More recently, with the advent of advances in computing, algorithms enabling machine learning, especially deep learning networks that mimic the human brain in function, there has been renewed interest to use them in clinical medicine. In cardiovascular medicine, AI-based systems have found new applications in cardiovascular imaging, cardiovascular risk prediction, and newer drug targets. [(Meng et al. 2020)](https://paperpile.com/c/8HuBlK/9H7w)These applications have led to newer treatment strategies for different types of cardiovascular diseases, newer approach to cardiovascular drug therapy and postmarketing survey of prescription drugs. However, there are several challenges in the clinical use of AI-based applications and interpretation of the results including data privacy, poorly selected/outdated data, selection bias, and unintentional continuance of historical biases/stereotypes in the data which can lead to erroneous conclusions. Still, AI is a transformative technology and has immense potential in health care. [(Mathur et al. 2020)](https://paperpile.com/c/8HuBlK/VjmO)

Cardiovascular imaging is going to change substantially in the next decade, fueled by the deep learning revolution. For medical professionals, it is important to keep track of these developments to ensure that deep learning can have a meaningful impact on clinical practice. This review aims to be a stepping stone in this process. The general concepts underlying most successful deep learning algorithms are explained, and an overview of the state-of-the-art deep learning in cardiovascular imaging is provided. This review discusses >80 papers[(Li et al. 2019)](https://paperpile.com/c/8HuBlK/S6Go), covering modalities ranging from cardiac magnetic resonance, computed tomography, and single-photon emission computed tomography, to intravascular optical coherence tomography and echocardiography. Many different machines learning algorithms were used throughout these papers, with the most common being convolutional neural networks. Recent algorithms such as generative adversarial models were also used. The potential implications of deep learning algorithms on clinical practice, now and in the near future, are discussed.[(Litjens et al. 2019)](https://paperpile.com/c/8HuBlK/tw1T)

In this work, the proposed new lightweight CNN architecture has improved the accuracy rate of cardiovascular disease classification to 98.23% compared with the existing state-of-the-art methods, using the dataset of ECG images of cardiac patients, and can be performed on a single CPU, overcoming the limitation of computational power.[(Suri et al. 2022)](https://paperpile.com/c/8HuBlK/cqnI) In addition, the classification accuracy has significantly improved after applying the proposed method as a feature extraction tool for traditional machine learning algorithms. For example, an accuracy of 99.79% has been achieved using the Naïve Bayes algorithm. Thus, this method could be integrated into the IoT ecosystem in healthcare. This will encourage other AI researchers to explore other methods for cardiovascular disease detection.

In this paper, we have presented an automatic LV function and mass quantification method by using deep learning networks. Unlike previous approaches, our proposal makes use of the Generalized Jaccard distance as objective loss function and residual learning strategies level-to-level to provide a suitable approach for myocardial segmentation and cardiac functional quantification.[(Curiale et al. 2019)](https://paperpile.com/c/8HuBlK/9DnV)

## III. Proposed Methodology

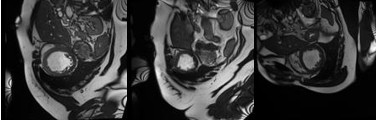


Fig 1: Sample Defected MRI of heart

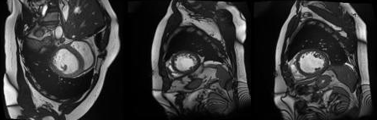


Fig 2: Sample Normal MRI of heart

Fig 1 and Fig 2 shows the sample images of the patient who is suffering from cardiovascular condition and other side is the normal person without any complications

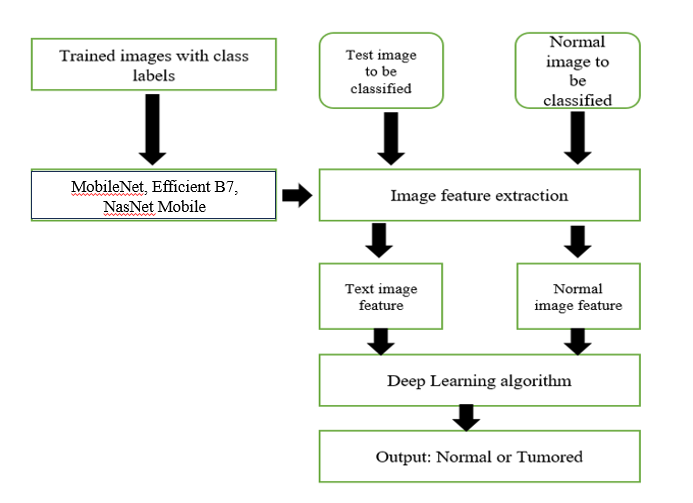


Fig 3: Proposed Flow Diagram

Fig 3 shows the flow diagram for proposed methodology

The proposed methodology utilizes MobileNet, Efficient Net B7, NasNet MobileLarge for classification of cardiovascular condition, specifically distinguishing between normal and those affected by cardiovascular condition.[(Cheung et al. 2021)](https://paperpile.com/c/8HuBlK/TLsW) The dataset is pre-processed to resize to 150x150 pixels and normalize the pixel values for increasing training efficiency. It contains an equal number of photos of normal and cardiovascular condition images. Rotation, zooming, flipping both vertically and horizontally, and other data augmentation techniques used to improve model generalization and avoid overfitting. Pretrained on ImageNet, MobileNet, Efficient Net B7, NasNet MobileLarge [(Bhongade et al. 2024)](https://paperpile.com/c/8HuBlK/R7E5)is used as a feature extractor. Transfer learning is used to refine the architecture, substituting bespoke layers for binary classification for fully connected levels.

In Fig 3, a deep CNN based on MobileNet, Efficient Net B7, NasNet MobileLarge was used for classification, and transfer learning was performed using defected and normal images.[(Ali et al. 2023)](https://paperpile.com/c/8HuBlK/damy) After retraining, the last layer of the network (classification layer) was removed, and the model was regarded as an image feature extractor.

Framework of the proposed approach. Fig 3 is the process of training and Fig 4 is the process of feature extraction and classification. diagram on the far right is a visual representation of Fig 4

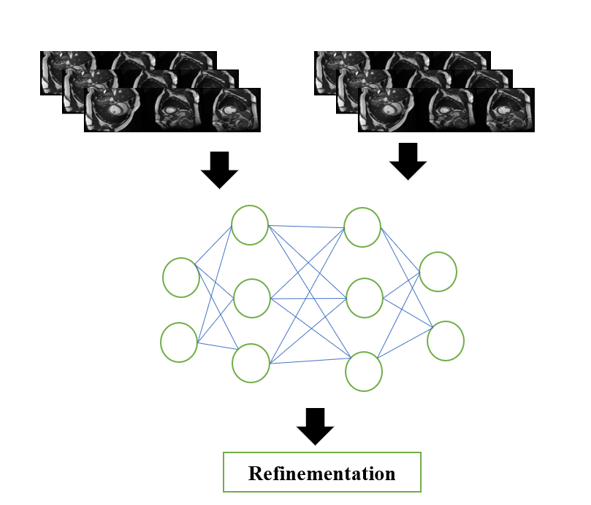


Fig 4: The feature extraction and classification

# IV. Result & Discussion

TABLE 1: Classification Report for

MobileNet

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameters | Precision | Recall | F1 | Support |
| AMD | 0.76 | 0.82 | 0.79 | 50 |
| Normal | 0.67 | 0.58 | 0.82 | 31 |
| Accuracy |  |  | 0.73 | 81 |
| Macro Avg | 0.71 | 0.70 | 0.70 | 81 |
| Weighted Avg | 0.72 | 0.73 | 0.72 | 81 |

Table 1 shows the classification models precision, recall and F1 score were 0.79 and 0.82 for both classes, and its ac was 72%

The MobileNet has able to gain the accuracy of only 72% after performing over 50 epochs and it is compared to the MobileNet, and the accuracy is compared accordingly

TABLE 2: Classification Report for

EfficientNetB7

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameters | Precision | Recall | F1 | Support |
| AMD | 0.86 | 0.12 | 0.21 | 54 |
| Normal | 0.41 | 0.97 | 0.57 | 31 |
| Accuracy |  |  | 0.44 | 81 |
| Macro Avg | 0.63 | 0.54 | 0.39 | 81 |
| Weighted Avg | 0.68 | 0.44 | 0.35 | 81 |

Table 2 shows the classification models precision, recall and F1 score were 0.12 and

0.97for both classes, and its ac was 44%

TABLE 3: Classification Report for

NasNet Mobile

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameters | Precision | Recall | F1 | Support |
| AMD | 0.88 | 0.60 | 0.71 | 50 |
| Normal | 0.57 | 0.87 | 0.69 | 31 |
| Accuracy |  |  | 0.70 | 81 |
| Macro Avg | 0.73 | 0.74 | 0.70 | 81 |
| Weighted Avg | 0.76 | 0.70 | 0.71 | 81 |

Table 3 shows the classification models precision, recall and F1 score were 0.71 and

0.69 for both classes, and its ac was 70%

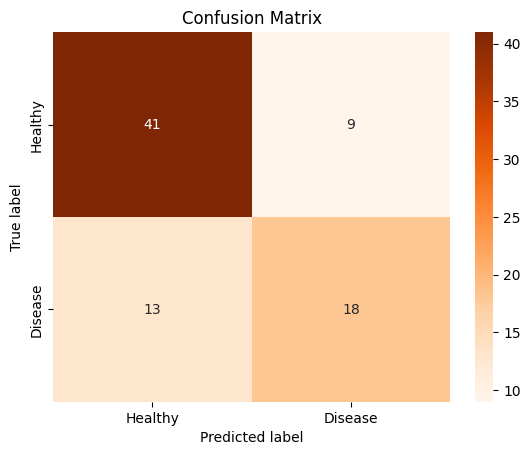


Fig 5: Confusion matrix for MobileNet

Fig 5 shows the confusion matrix for the MobileNet model. It demonstrates good performance in differentiating between Tumor (disease) and Normal (healthy) with 18 true positive (TP) for Tumar, 41 true negative (TN) for Normal cases, 9 for false positives (FP), and 13 for false negative (FN).

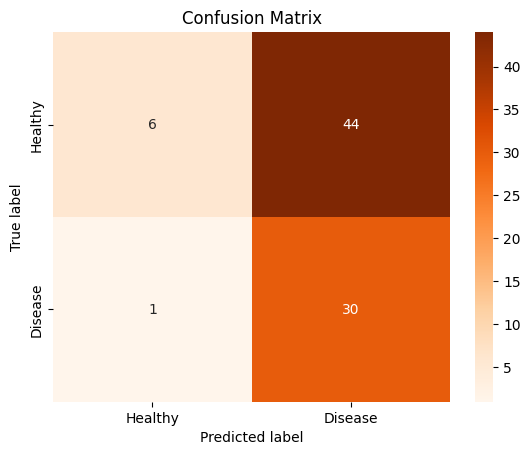


Fig 6: Confusion matrix for MobileNet

Fig 6 shows the confusion matrix for the EfficientNetB7 model. It demonstrates good performance in differentiating between Tumar (disease) and Normal (healthy) with 30 true positive (TP) for AMD, 6 true negative (TN) for Normal cases, 44 for false positives (FP), and 1 for false negative (FN).

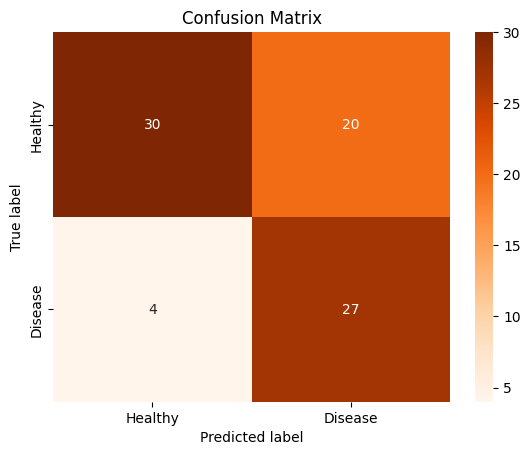


Fig 7: Confusion matrix for MobileNet

Fig shows the confusion matrix for the EfficientNetB7 model. It demonstrates good performance in differentiating between Tumar (disease) and Normal (healthy) with 27 true positive (TP) for AMD, 30 true negative (TN) for Normal cases, 20 for false positives (FP), and 4 for false negative (FN).

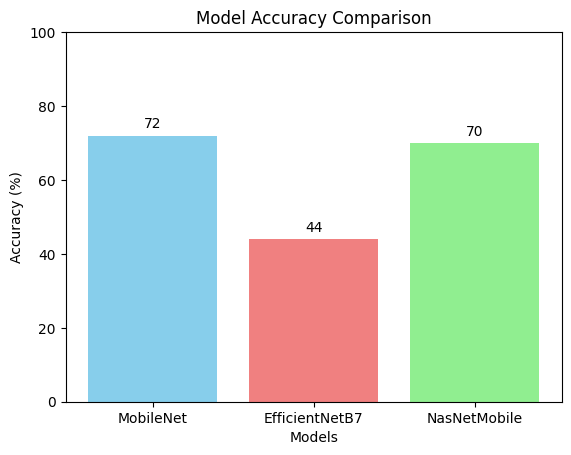


Fig 8: Accuracy comparison of Mobile net, EfficientNetB7,NasNetMobile

Fig 8 shows the accuracy comparison of ResNet101 and ResNet101V2 models, with the first model achieving 47.69% of accuracy and second model achieving 98.46% of accuracy

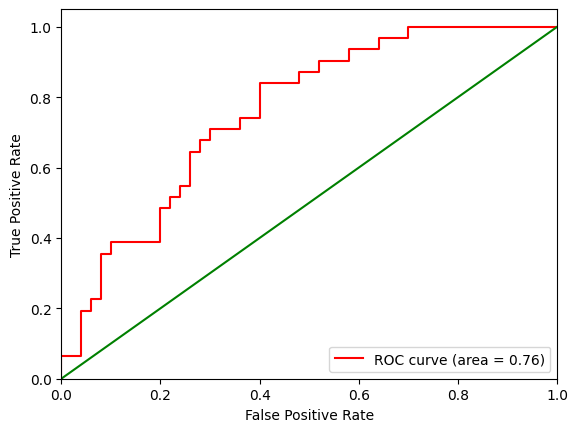


Fig 9: ROC curve for MobileNet

Fig 9 shows the ROC curve for the MobileNet model for the tumor detection; the red line indicates that the receiver operating characteristics (ROC) are 0.76. It plots the true positive and false positive rates to demonstrate the model’s performance

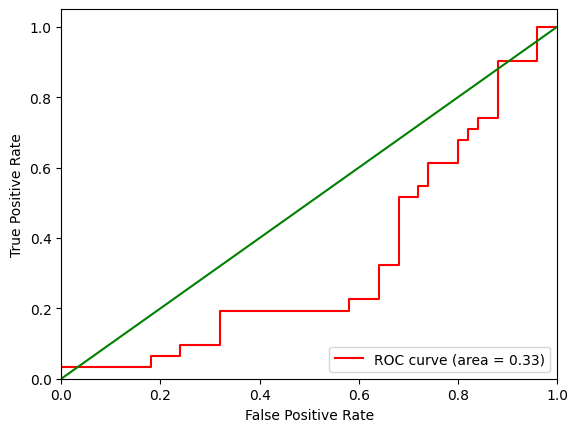


Fig 10: ROC curve for EfficientNetB7

Fig 10 shows the ROC curve for the EfficientNetB7 model for the Tumor detection; the red line indicates that the receiver operating characteristics (ROC) are 1.00. It plots the true positive and false positive rates to demonstrate the model’s performance

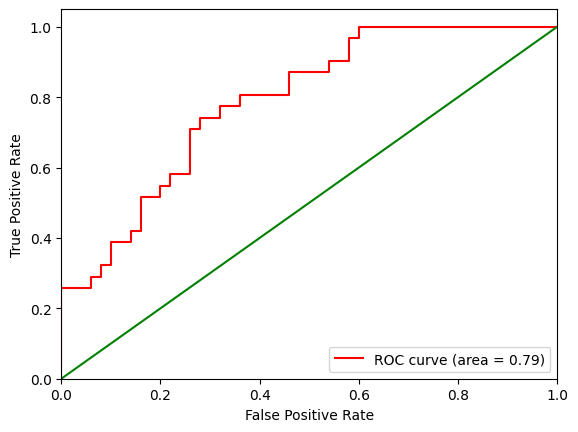


Fig 11: ROC curve forNasNetMobile

Fig 11 shows the ROC curve for the EfficientNetB7 model for the Tumor detection; the red line indicates that the receiver operating characteristics (ROC) are 0.79 It plots the true positive and false positive rates to demonstrate the model’s performance

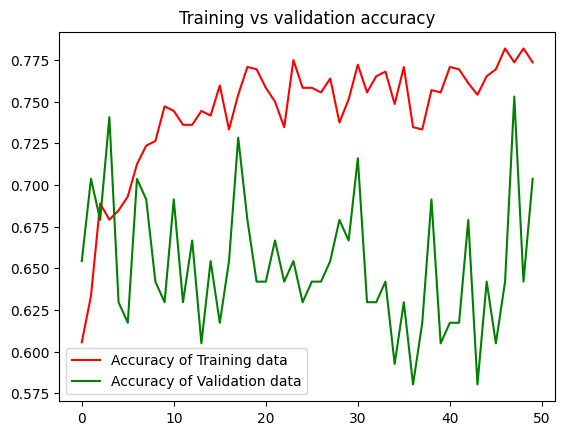


Fig 12: Accuracy curve for MobileNet

Fig 12 shows the accuracy curve for AMD Disease Detection using MobileNet across 50 epochs. The blue line indicates an accuracy of 72% on the validation data, while the red line shows an accuracy of 72.69 on the training data. The tight alignment of these curves indicates that the model has successfully captured the patterns in the dataset and is well-optimized. Additionally, the excellent accuracy on both training and validation sets suggests that there is no overfitting, which is advantageous for deep learning models when handling challenging tasks like illness diagnosis.

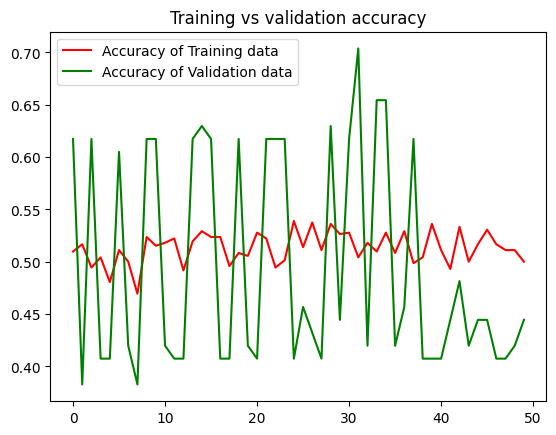


Fig 13: Accuracy curve for EfficientNetB7

Fig 13 shows the accuracy curve for Tumar Disease Detection using EfficientNetB7 across 50 epochs. The blue line indicates an accuracy of 44% on the validation data, while the red line shows an accuracy of 44.69 on the training data. The tight alignment of these curves indicates that the model has successfully captured the patterns in the dataset and is well-optimized. Additionally, the excellent accuracy on both training and validation sets suggests that there is no overfitting, which is advantageous for deep learning models when handling challenging tasks like illness diagnosis.

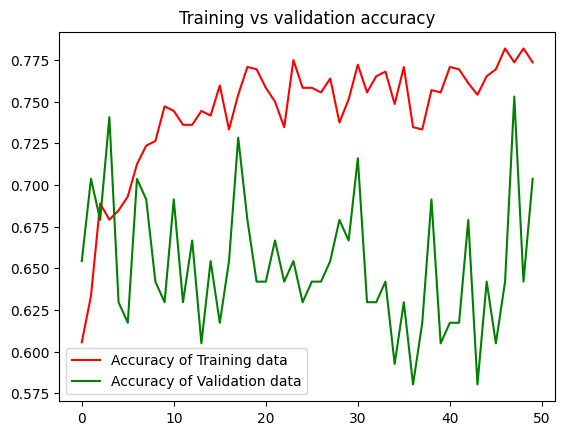


Fig 14: Accuracy curve for NasNet Mobile

Fig 14 shows the accuracy curve for AMD Disease Detection using NasNet Mobile across 50 epochs. The blue line indicates an accuracy of 70% on the validation data, while the red line shows an accuracy of 70.69 on the training data. The tight alignment of these curves indicates that the model has successfully captured the patterns in the dataset and is well-optimized. Additionally, the excellent accuracy on both training and validation sets suggests that there is no overfitting, which is advantageous for deep learning models when handling challenging tasks like illness diagnosis.

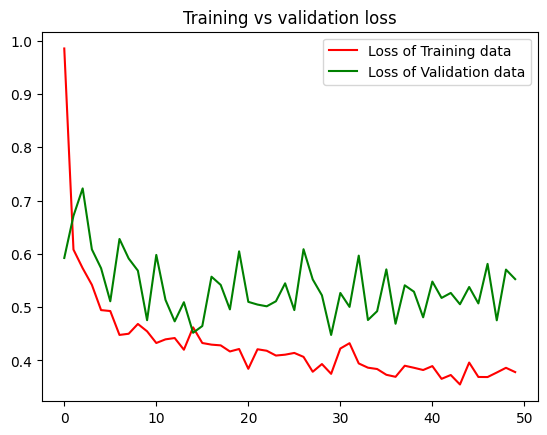


Fig 15: Loss curve for ResNet50

Fig 15 shows the loss curve for AMD detection using MobileNet across 50 epochs. The model is effectively learning and modifying its parameters, as shown by the red line that displays validation loss, also shows an ongoing downward trend over the epochs. Based on the concurrent decrease in training and validation loss, the model seems to be generalizing well, capturing the important data features without overfitting.

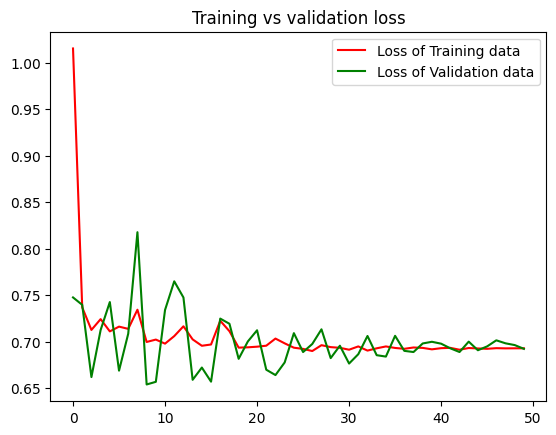


Fig 16: Loss curve for EfficientNetB7

Fig 16 shows the loss curve for AMD detection using EfficientNetB7 across 50 epochs. The model is effectively learning and modifying its parameters, as shown by the red line that displays validation loss, also shows an ongoing downward trend over the epochs. Based on the concurrent decrease in training and validation loss, the model seems to be generalizing well, capturing the important data features without overfitting.

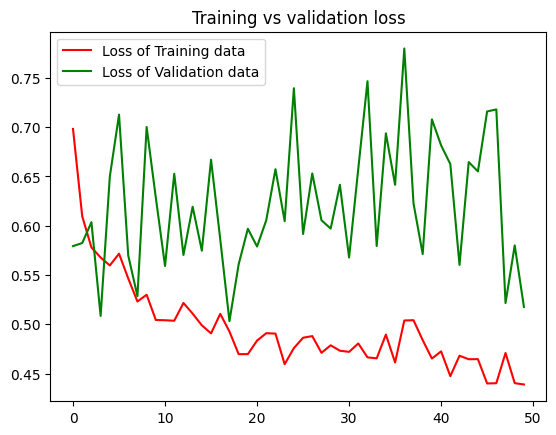


Fig 17: Loss curve for NasNetMobile

Fig 17 shows the loss curve for AMD detection using NasNetMobile across 50 epochs. The model is effectively learning and modifying its parameters, as shown by the red line that displays validation loss, also shows an ongoing downward trend over the epochs. Based on the concurrent decrease in training and validation loss, the model seems to be generalizing well, capturing the important data features without overfitting.

# V. Conclusion

MobileNet exhibits an impressive 72.69% accuracy rate.[(Estimation of Prediction for Heart Fa...)](https://paperpile.com/c/8HuBlK/5saU) Its architecture, which effectively balances processing economy and accuracy, makes it ideal for applications requiring exact classification.[(Zarkogianni et al. 2018)](https://paperpile.com/c/8HuBlK/DdWG) EfficientNetB7, which attains a lower accuracy of 44.92%, and the NasNetMobile stands in second with accuracy of 70% despite being designed for lightweight applications. [(Pawar et al. 2024)](https://paperpile.com/c/8HuBlK/RYzY)

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