Deep Learning Approaches for Cardiac MRI and Heart Disease Estimation using ResNet101, DenseNet169,NASNET Large

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Abstract:

**Heart disease is the most common cause and also the leading cause of mortality in the general population of death in patients with cardiac problems. Advances in noninvasive cardiovascular conditions imaging have improved early detection of subclinical disease. The goals of medical management of cardiac disease are to modify the natural detection of disease . Traditional diagnostic techniques, however, can be laborious and may need to be interpreted by a specialist. In this case, the deep algorithm plays a crucial part in identifying cardiac illness from MRI images. which uses the ResNet101, DenseNet169, and NASNET Large algorithms to enable each person with cardiac illness to understand the risk factors for their condition. We offer an automated and effective method of estimating cardiac illness by combining these cutting-edge approaches, which eventually aids in improved clinical decision-making.**

**Keywords:**

*ResNet101,DenseNet169,NASNET Large,MRI images,cardiovascular conditions imaging*

# I. Introduction

Heart disease, or cardiovascular disease, is the world's largest cause of mortality, according to the World Health Organization. An estimated 17.9 million people are killed by them annually, making up 32% of all fatalities globally. Heart attacks, sometimes referred to as myocardial infarctions (MI), account for over 85% of all heart disease-related deaths. Early detection and effective diagnosis of cardiovascular disease can save many lives. The healthcare system uses a variety of methods, including computed tomography, cardiac magnetic resonance imaging, echocardiogram (echo), blood testing, and more, to identify heart conditions.[(Awan et al. 2018)](https://paperpile.com/c/AXLijZ/ybSK)

Advances in artificial intelligence have enormous promise to improve healthcare and lower medical errors. Specifically, the automatic prediction of heart illnesses by the use of machine learning and deep learning techniques. [(Pawar et al. 2024)](https://paperpile.com/c/AXLijZ/cWoo)Before implementing the classification phase, the machine learning techniques need an expert entity for feature extraction and selection in order to find the right features. By converting or projecting the data into a new, lower-dimensional feature space while maintaining the pertinent information of the input data, feature extraction reduces the amount of features in a data collection.[(Al'Aref et al. 2019)](https://paperpile.com/c/AXLijZ/sb12) On the other hand, deep learning, which is subfield of machine learning, automatically extracts important features and patterns from the training datasets for the classification phase without the intervention of separate entities for features extraction and selection

# II. Related Work

The rapid digitalization of healthcare presents itself with the opportunity to tackle important medical questions using ML. While traditional statistical methods remain the *lingua* franca of medical research, ML proposes a novel toolset for navigating a rapidly shifting landscape. Additionally, ML could provide a powerful platform for integration of clinical and imaging data, which would be useful for multifactorial and complex cardiovascular diseases such as heart failure. In this review, we highlight the recent applications of ML within cardiovascular medicine, with emphasis on cardiac imaging. ML promises to transform medical research which could lead to optimization of day-to-day clinical workflow while improving risk assessment and potentially outcomes.[(Al'Aref et al. 2019)](https://paperpile.com/c/AXLijZ/sb12)

Identifying the processing of raw healthcare data of heart information will help in the long term saving of human lives and early detection of abnormalities in heart conditions. Machine learning techniques were used in this work to process raw data and provide a new and novel discernment towards heart disease. Heart disease prediction is challenging and very important in the medical field. However, the mortality rate can be drastically controlled if the disease is detected at the early stages and preventative measures are adopted as soon as possible. Further extension of this study is highly desirable to direct the investigations to real-world datasets instead of just theoretical approaches and simulations. The proposed hybrid HRM approach is used combining the characteristics of Random Forest (RF) and Linear Method (LM).[(Gonsalves et al. 2019)](https://paperpile.com/c/AXLijZ/qyRb) HR FILM proved to be quite accurate in the prediction of heart disease. The future course of this research can be performed with diverse mixtures of machine learning techniques to better prediction techniques. Furthermore, new feature-selection methods can be developed to get a broader perception of the significant features to increase the performance of heart disease prediction.[(Mohan et al. 2019)](https://paperpile.com/c/AXLijZ/7PU8)

The accurate classification rates of Coronary Heart disease, the RF model outperformed the SVM and LR models. Also, the RF model had the highest sensitivity value. We think that this result, which has a high sensitivity criterion in order to minimize overlooked heart patients, is clinically very important.[(Yilmaz and Yağin 2021)](https://paperpile.com/c/AXLijZ/YdeY)

The performance of the proposed approach to human performance, we conducted a two-round reader study. In the experiments, the performance was evaluated by both FROC analysis and calcium mass quantification analysis on a set of 840 FFDM images from 210 cases. The FROC analysis shows that the proposed approach obtains FPs of 0.4762 cm2 with a TP rate of 60%, comparable to the performance of at least one of the readers. [(Wang et al. 2017)](https://paperpile.com/c/AXLijZ/xzWO)

According to the authors, the medical sector for deep learning applications has grown thanks to deep learning models. To select most attributes, traditional machine learning algorithms in expected fields. For learning algorithm to function well, this lowers the complexity of the data and increase the visibility of the pattern. Implementing the wide range of machine learning models has allowed for the classification and detection of diseases. Advance in particular area of machine learning known as deep learning use hierarchically constructed artificial neural networks to speed up the process of machine learning[(Tripoliti et al. 2017)](https://paperpile.com/c/AXLijZ/UO5X)

## III. Proposed Methodology

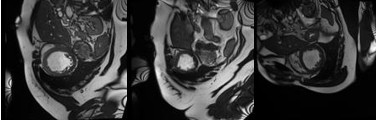


Fig 1: Sample Defected MRI of heart

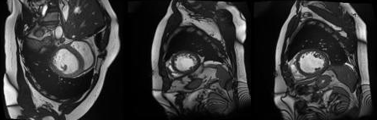


Fig 2: Sample Normal MRI of heart

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

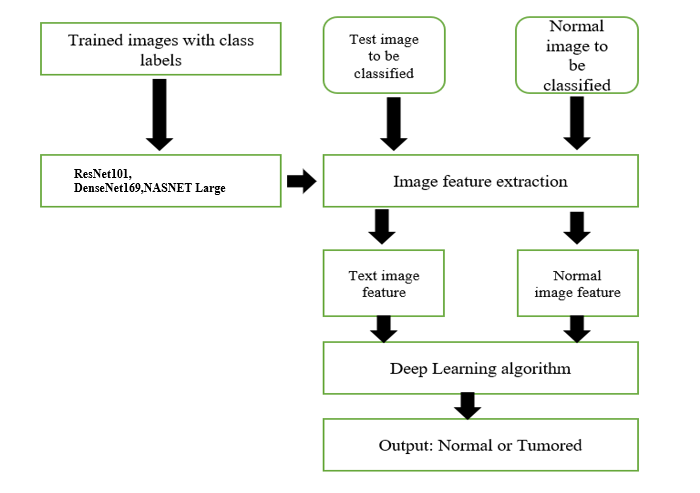


Fig 3: Proposed Flow Diagram

Fig 3 shows the flow diagram for proposed methodology

The proposed methodology utilizes ResNet101, DenseNet169 and NASNET Large for classification of cardiovascular condition, specifically distinguishing between normal and those affected by cardiovascular condition.[(Joo et al. 2020)](https://paperpile.com/c/AXLijZ/hwj6) 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.[(Jing et al. 2020)](https://paperpile.com/c/AXLijZ/a5Bn) Rotation, zooming, flipping both vertically and horizontally, and other data augmentation techniques used to improve model generalization and avoid overfitting. Pretrained on ImageNet, ResNet101, DenseNet169 and NASNET Large is used as a feature extractor. [(Mehmood et al. 2021)](https://paperpile.com/c/AXLijZ/N2uz)Transfer learning is used to refine the architecture, substituting bespoke layers for binary classification for fully connected levels. The modelsResNet101, DenseNet169 and NASNET Large are trained across 50 epochs using binary cross-entropy loss and the Adam optimizer. The model’s performance is evaluated using several metrics, such as accuracy, precision, recall, F1-score and ROC-AUC. [(Saw et al. 2020)](https://paperpile.com/c/AXLijZ/eLeE)

In Fig 3, a deep CNN based onResNet101, DenseNet169 and NASNET Large was used for classification, and transfer learning was performed using Tumor and normal images. After retraining, the last layer of the network (classification layer) was removed, and the model was regarded as an image feature extractor.[(Amarbayasgalan et al. 2019)](https://paperpile.com/c/AXLijZ/D6FN)

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

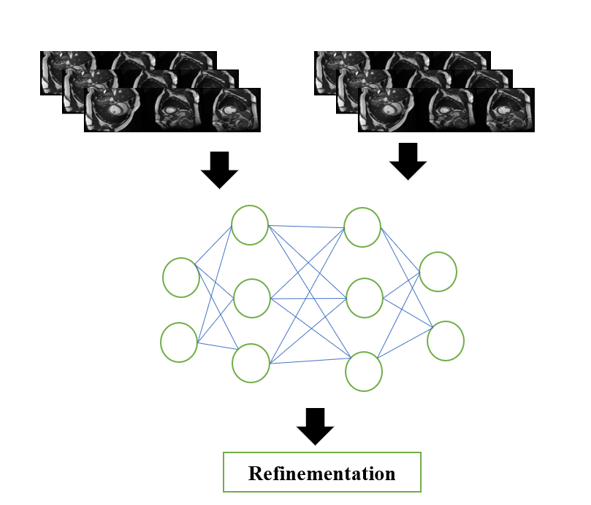


Fig 4: The feature extraction and classification

# IV. Result & Discussion

TABLE 1: Classification Report for

ResNet101

| Parameters | Precision | Recall | F1 | Support |
| --- | --- | --- | --- | --- |
| AMD | 0.88 | 0.46 | 0.61 | 50 |
| Normal | 0.51 | 0.90 | 0.65 | 31 |
| Accuracy |  |  | 0.63 | 81 |
| Macro Avg | 0.70 | 0.68 | 0.63 | 81 |
| Weighted Avg | 0.74 | 0.63 | 0.62 | 81 |

Table 1 shows the classification models precision, recall and F1 score were 0.61 and 0.46 for both classes, and its ac was 54%

The ResNet101 has able to gain the accuracy of only 54% after performing over 50 epochs and it is compared to the ResNet101, and the accuracy is compared accordingly

TABLE 2: Classification Report for

DenseNet169

| Parameters | Precision | Recall | F1 | Support |
| --- | --- | --- | --- | --- |
| AMD | 0.82 | 0.62 | 0.70 | 50 |
| Normal | 0.56 | 0.77 | 0.65 | 31 |
| Accuracy |  |  | 0.68 | 81 |
| Macro Avg | 0.69 | 0.70 | 0.68 | 81 |
| Weighted Avg | 0.72 | 0.68 | 0.68 | 81 |

Table 2 shows the classification models precision, recall and F1 score were 0.70 and

0.65 for both classes, and its ac was 67%

TABLE 3: Classification Report for

NasNet Large

| Parameters | Precision | Recall | F1 | Support |
| --- | --- | --- | --- | --- |
| AMD | 0.82 | 0.66 | 0.73 | 50 |
| Normal | 0.590 | 0.77 | 0.67 | 31 |
| Accuracy |  |  | 0.70 | 31 |
| Macro Avg | 0.71 | 0.72 | 0.70 | 81 |
| Weighted Avg | 0.73 | 0.70 | 0.71 | 81 |

Table 2 shows the classification models precision, recall and F1 score were 0.70 and

0.67 for both classes, and its ac was 70% which concludes the highest among other two algorithms

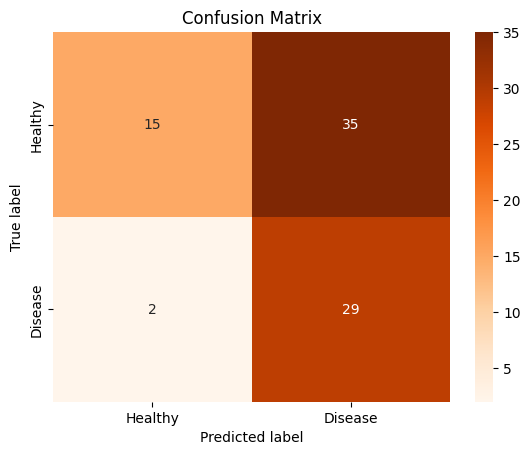


Fig 5: Confusion matrix for ResNet101

Fig 5 shows the confusion matrix for the ResNet101 model. It demonstrates good performance in differentiating between Tumor (disease) and Normal (healthy) with 29 true positive (TP) for Tumar, 15 true negative (TN) for Normal cases, 35 for false positives (FP), and 2 for false negative (FN).

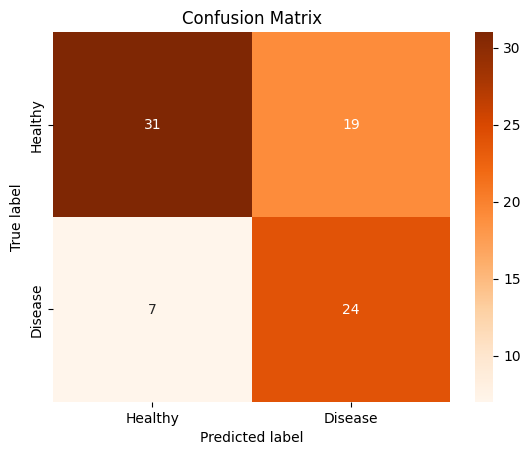


Fig 6: Confusion matrix for DenseNet169

Fig 6 shows the confusion matrix for the MobileNet model. It demonstrates good performance in differentiating between Tumar (disease) and Normal (healthy) with 24 true positive (TP) for AMD, 31 true negative (TN) for Normal cases, 19 for false positives (FP), and 7 for false negative (FN).

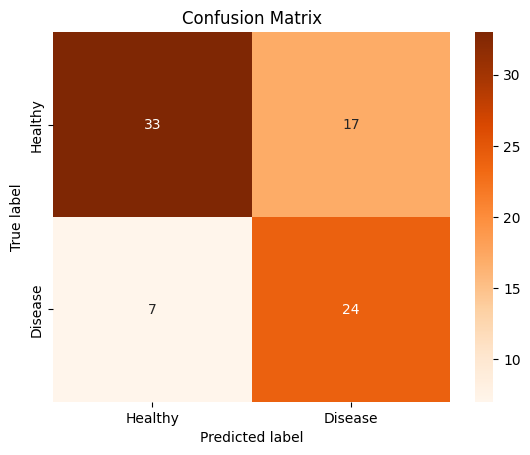


Fig 7: Confusion matrix for NasNet Large

Fig 7 shows the confusion matrix for the MobileNet model. It demonstrates good performance in differentiating between Tumar (disease) and Normal (healthy) with 24 true positive (TP) for AMD, 33 true negative (TN) for Normal cases, 17 for false positives (FP), and 7 for false negative (FN).

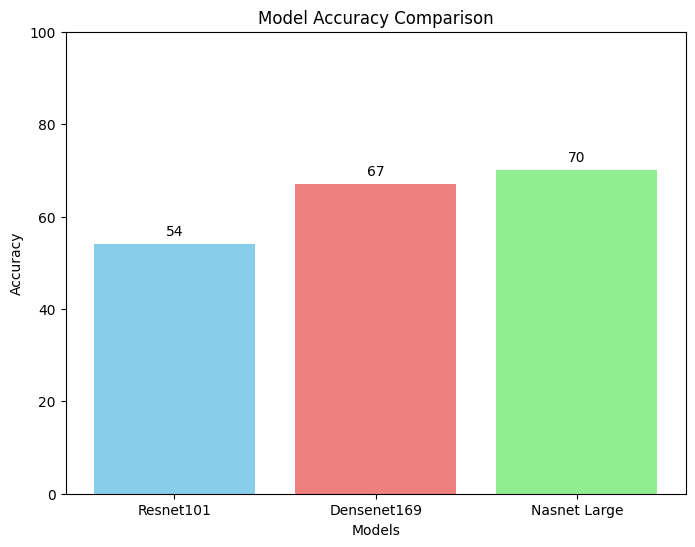


Fig 8: Accuracy comparison of ResNet101,DenseNet169 and NasNet Large

Fig 8 shows the accuracy comparison of ResNet101,DenseNet169 and NasNet Large models, with the first model achieving 54.69% of accuracy and second model achieving 67.46% of accuracy and third model achieving 70% of accuracy

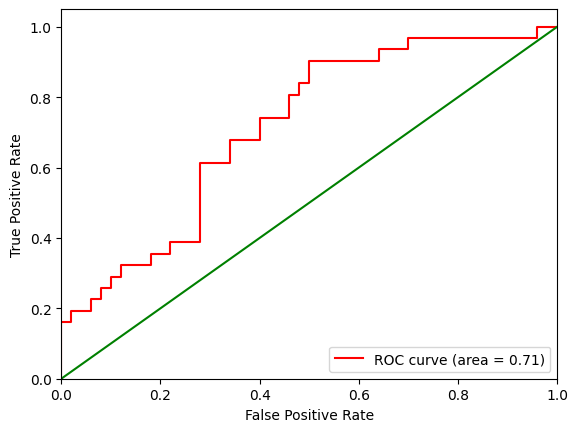


Fig 9: ROC curve for ResNet101

Fig 9 shows the ROC curve for the ResNet101 model for the tumor detection; the red line indicates that the receiver operating characteristics (ROC) are 0.71. It plots the true positive and false positive rates to demonstrate the model’s performance

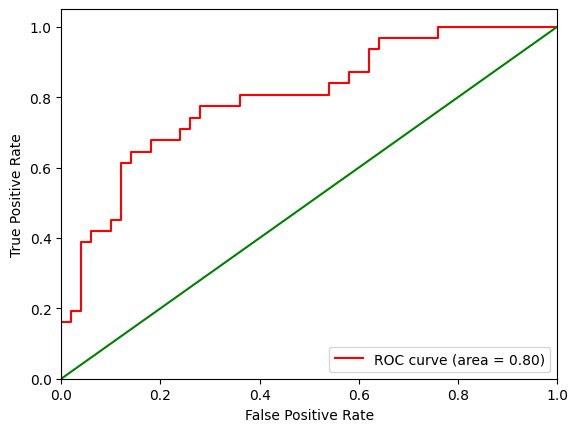


Fig 10: ROC curve for DenseNet169

Fig 10 shows the ROC curve for the DenseNet169 model for the Tumor detection; the red line indicates that the receiver operating characteristics (ROC) are 0.80. It plots the true positive and false positive rates to demonstrate the model’s performance

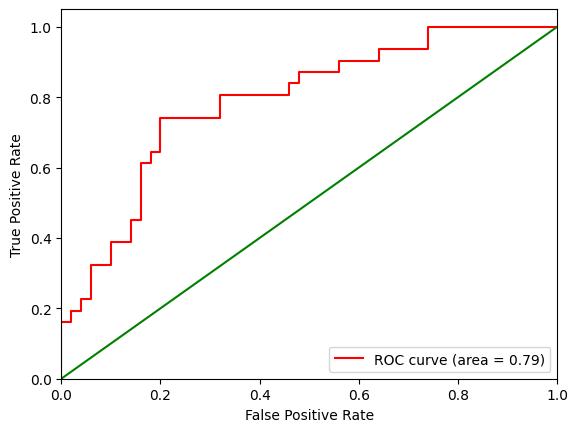


Fig 11: ROC curve for NasNet Large

Fig 11 shows the ROC curve for the NasNet Large 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

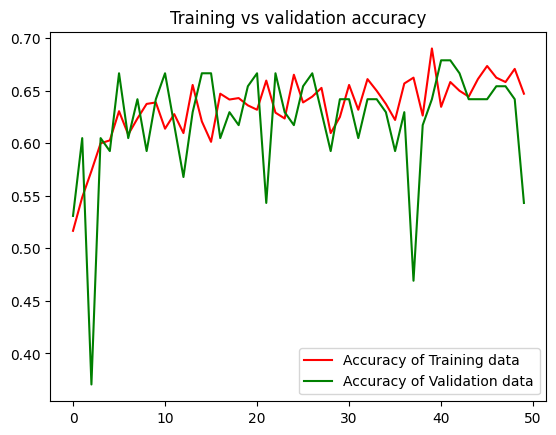


Fig 12: Accuracy curve for ResNet101

Fig 12 shows the accuracy curve for AMD Disease Detection using ResNet101 across 50 epochs. The blue line indicates an accuracy of 54% on the validation data, while the red line shows an accuracy of 54.69 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.

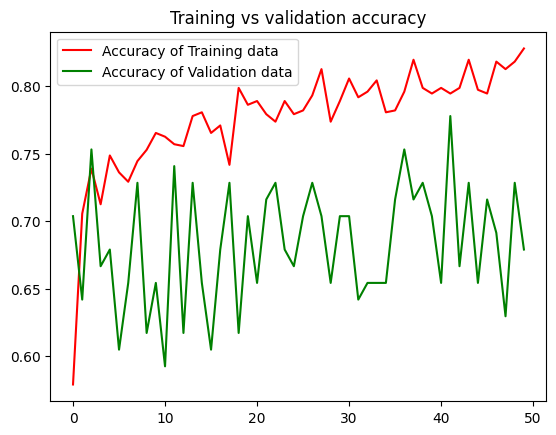


Fig 13: Accuracy curve for DenseNet

Fig 13 shows the accuracy curve for Tumar Disease Detection using MobileNet across 50 epochs. The blue line indicates an accuracy of 67% on the validation data, while the red line shows an accuracy of 67.69 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.

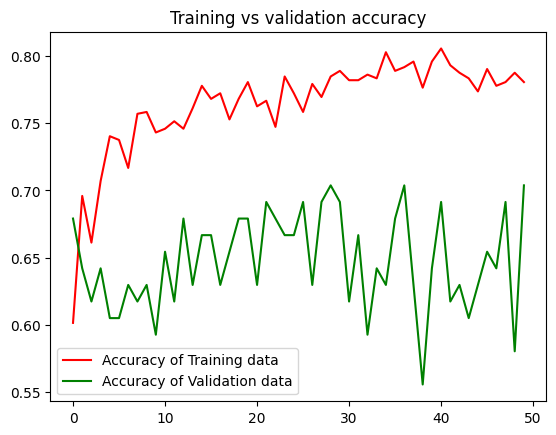


Fig 14: Accuracy curve for DenseNet

Fig 14 shows the accuracy curve for Tumar Disease Detection using MobileNet 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.

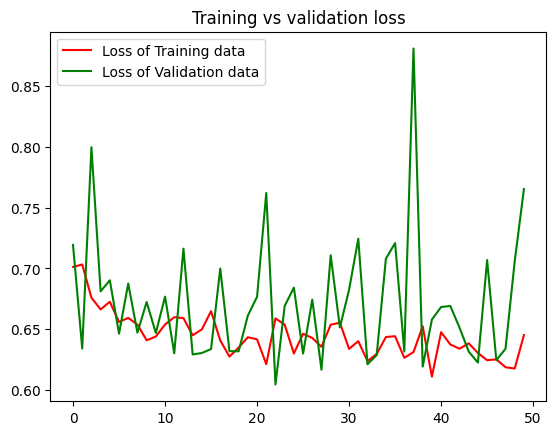


Fig 15: Loss curve for ResNet101

Fig 15 shows the loss curve for AMD detection using ResNet101 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.

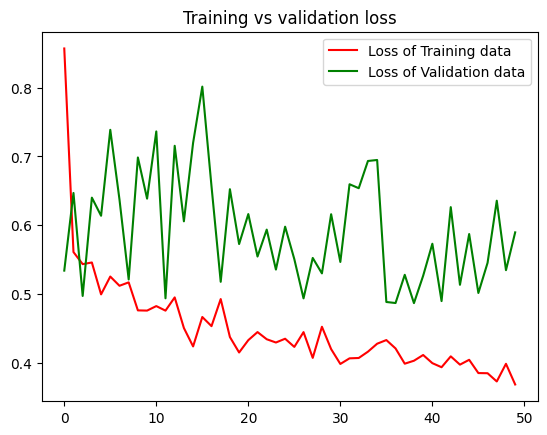


Fig 16: Loss curve for DenceNet169

Fig 16 shows the loss curve for AMD detection using DenseNet169 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.

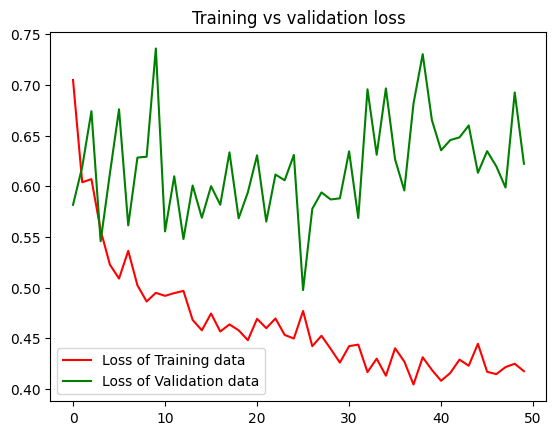


Fig 17: Loss curve for NasNet Large

Fig 17 shows the loss curve for AMD detection using NasNet Large 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

NasNet Large exhibits an impressive 70.69% accuracy rate. Its architecture, which effectively balances processing economy and accuracy[(Katarya and Meena 2021)](https://paperpile.com/c/AXLijZ/WFKF), makes it ideal for applications requiring exact classification. ResNet101, which attains a lower accuracy of 54.92% and DenseNet169 gives the accuracy of 69% despite being designed for lightweight applications. [(Javaid et al. 2022)](https://paperpile.com/c/AXLijZ/ghBg)

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