Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 6, July, 2021: 5124 - 5134

Detection and Prediction of Cardiac Amyloidosis disease using deep learning algorithms- Comparative Study

[*1]Gladys Jebakumari.G
Research Scholar
Vels Institute of Science Technology and Advanced Studies, Tamilnadu, India.
gladysjebakumari001@gmail.com
[2]Dr.Arun Raaza
Deputy Director
Centre for Advanced Research and Development
Vels Institute of Science Technology and Advanced Studies, Tamilnadu, India.
arunraaza@gmail.com

Abstract-Extracellular deposition of amyloid fibrils within the heart greatly expands the extracellular volume in Cardiac Amyloidosis (CA). Patients who are affected with CA disease have significant heart failure and have a poor prognosis too. To resolve these issues, this paper mainly focused on deep learning based classification algorithm such as VGG-16, VGG-19, Xception model and DenseNet201 approach for predicting heart disease especially CA using ECG images. Moreover, metrics such as precision, recall, F1-score and accuracy are estimated to find the performance of deep learning models in CA disease diagnosis. Our experimental outcomes show that DenseNet201 model attains higher accuracy of 92.86% in disease identification and classification too.
Keywords-*Cardiac Amyloidosis (CA), VGG-16, VGG-19, Xception model, Comparative analysis and ResNet model.*

1. Introduction

Cardiac Amyloidosis is mayhem caused by setting down excess of proteins in the tissues of the heart. These deposits formulate the heart not to functioning appropriately. Hence several researchers found that machine learning technique generate better enhancement in predicting Cardiac Amyloidosis based on monitoring the parameters continuously done by Agibetov et. al [1]. Since monitoring features is not enough in identifying the heart disease so we are implementing deep learning based pre-trained models such as VGG-16, VGG-19, Xception, and DenseNet 201 models for diagnosing heart disease especially CA disease which helps to identify the disease earlier by taking ECG of heart for better curing from that specific disease[21].

The main objective of this research work is described as follows

- To gather heart-based Electrocardiogram (ECG) images.
- To analyze the infection or injury in heart from heart diagnose images namely ECG, MRI, and X-ray images.
- To build deep learning based pre-trained models such as VGG-16, VGG-19, Xception and DenseNet201 model for detecting Cardiac Amyloidosis disease.

- To measure the efficacy of deep learning models for heart disease diagnosis, metrics such as accuracy, precision, recall, and F1 score will be useful for clinical assessment and disease prediction.

This paper evaluates the accuracy of deep based pre-trained algorithms in diagnosing heart disease on images and categorizing the images into normal from abnormal which is considered as Cardiac Amyloidosis. And finally, comparison had done for predicting which algorithm produced better outcomes in finding disease.

2. Related works

Huda et. al [7] determined that machine learning algorithms especially random forest method are appropriate for finding the threat of heart malfunction because of Transthyretin amyloid cardiomyopathy. Duca et. al [3] discussed that evaluation of Extra Cellular Volume (ECV) using Cardiac Magnetic Resonance beside histological ECV in Cardiac Amyloidosis helps to identify the risk of heart disease. Escamilla et. al [8] focused on feature collection approach for selecting the features on heart images to identify heart disease and also applied reduction dimensionality approach to diminish the features which are not necessitate. Here, Principle Component Analysis along with Chi-Square method achieved greater performance in detecting heart disease.

Brunese et. al [11] proposed deep learning based algorithms mainly layers in CNN approach detect the heart disease based on the features of heart beat sounds. Asmare et. al [12] introduced deep learning models for identifying Rheumatic based heart disease also categorizing normal heart images from abnormal based on spatial temporal version of non-partitioned heart beat sounds .Ghorbani et. al [6] explained that deep learning models applied to echocardiography can detect local heart outlines, assess heartutility, and predict systemic phenotypes that change cardiovascular risk but are not easily identified by human analysis using CNNs on a huge novel data.Awais et. al [2] introduced CardioHelp technique which helps to detect the possibility of availability of cardio vascular disease by integrating with deep based CNN approach. The accuracy reaches around 97% in predicting heart based cardiovascular disease. Gertz et. al [5] found the heart disease namely Immunoglobulin light chain Amyloidosis was identified and consequently the curing of specific disease was explained. Martini et. al [13] applied deep learning algorithm for detecting cardiac Amyloidosis disease using cardiac magnetic resonance images of heart that reaches an accuracy of 88% along with Area under Curve as 98%.

McVeigh et. al [14] explained about the how to realizeheart images and the way to identify cardiac Amyloidosis disease. Selviet. al [19] applied deep based neural network model for heart disease diagnosis and disease classification has done using KNN, Naïve Bayes and Random Forest. Scully et. al [18] identified the malfunction happened in the heart and replace the infection with transcatheter Aortic valve. Gokulan et. al [16], Narmatha et. al [4] and Kittleson et. al [9] described how CA disease is detected, categorize the normal images from abnormal and how to cure CA disease. Muhammad et. al [15] proposed intelligent computational approach for identifying heart disease very earlier and also accurately. Satriano et. al [17]The goal of this study was to see if a neural network trained with 3D-MDA could be used to automatically diagnose hypertrophic cardiomyopathy. Li et. al [10] utilized an approach based on markers which helps to point out the affected region of heart which is reported as Cardiac Amyloidosis. Zheng et al. [20] introduced the Convolutional Neural Network, which has several pre-trained models for detecting breast cancer disease using mammogram images, which are investigated by three cascading detectors such as Haar parameters, Local Binary Pattern, and Histogram of Oriented Gradient (HOG), which helps to identify the cancer affected region on patients' mammogram images.

3. Deep learning based pre-trained models

a. VGG-16

VGG-16 is one of the Convolutional neural network models that were utilized to succeed ImageNet model during the year 2014[22]. This is considered one of the best computer visualization frameworks available today. Instead of having a large number of hyper-parameters, VGG16 concentrated on having 3x3 filter convolution layers with a step 1 and always used the same padding and max-pooling layer of 2x2 filter steps 2. The convolution and max pool layers are positioned in the same way throughout the architecture shown in figure 1. It finishes with two FC (fully connected layers) and a SoftMax for output. The number 16 in VGG16 refers to the fact that it has 16 layers of varying weights. With an estimated 138 million parameters, this network is large.

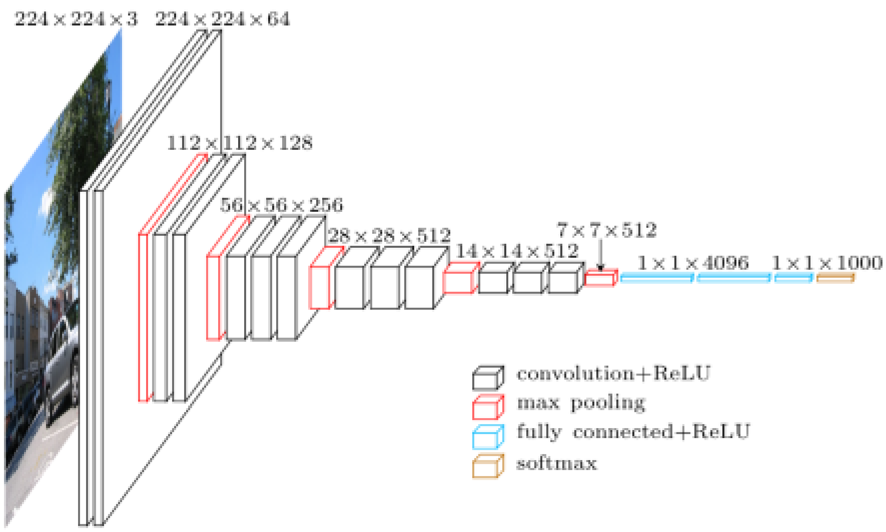

Figure 1. VGG-16 network architecture

Import all the libraries which are needed to implement VGG-16 neural network algorithm. Also, this architecture has 138 millions of features wholly. The goal of ImageDataGenerator is to make it simple to import data with labels into the model. It's a highly helpful class because it offers a lot of functions including resizing, rotating, zooming, and flipping. I'm making an ImageDataGenerator object for both training and testing data, and I'm sending the folder containing the training data to the object as “trdata” (training data), and the folder containing the test data to the object “tsdata” (testing data).

b. VGG-19

Simonyan and Zisserman from the University of Oxford created VGG-19, a deep learning-based CNN model with 19 layers. The ImageNet database can be used to load a pre-trained version of the network that has been trained on over a million images in the given domain. The network can categorize photographs into 1000 different object categories, such as keyboards, mouse, pencils, and other animals. As a result, the network has amassed a library of rich feature representations for a wide range of images. The picture input size for the network is 224 224 pixels. We are importing many heart photos in order to identify people with cardiac Amyloidosis illness. As a result, for a range of photos, the model has learned a number of rich feature representations[23][24]. R-CNN 31 is a region-based CNN that uses CNN to detect and classify objects after generating a region proposal.To speed up the process and improve accuracy, the Fast R-CNN32 and Fasted R-CNN33 algorithms are developed afterwards. The RCNN technique, on the other hand, is unsuitable for diagnosing heart illness because the quality and size of heart pictures varies greatly from case to case. As a result, we're using the VGG-19 model, which is represented in Figure 2, to upload patient's heart MRI scans for disease diagnosis.

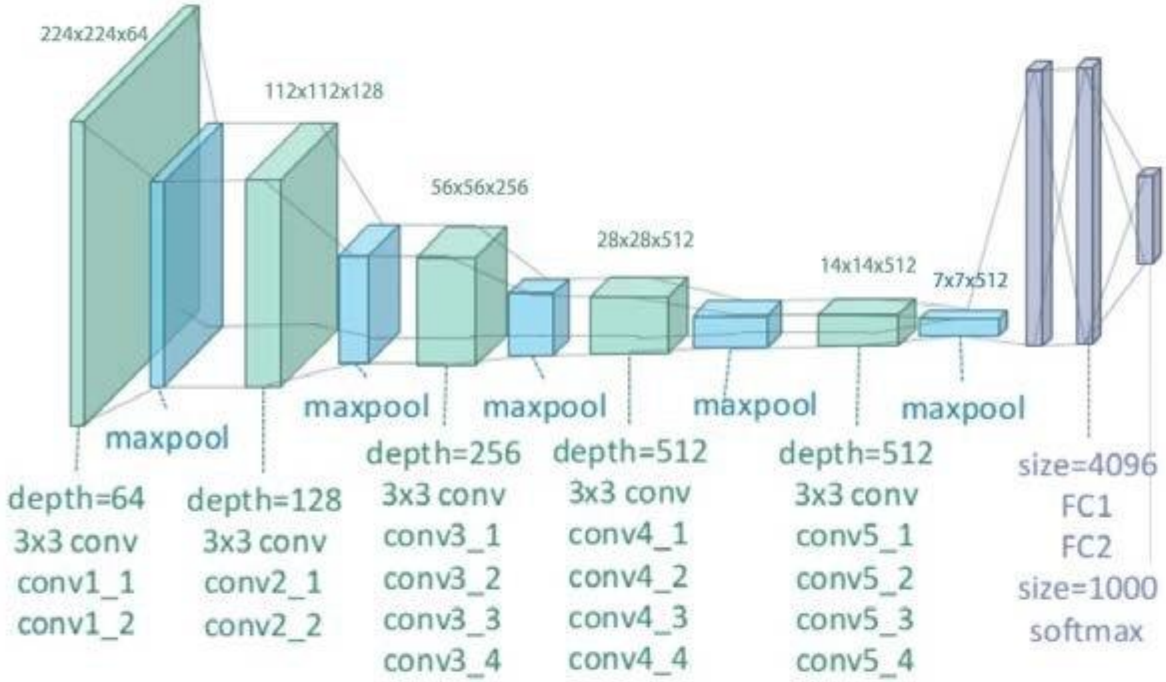

Figure 2. VGG-19 network framework

Some features along with its creation of objects are used to perform operations in finding disease using VGG-19 model as follows

- Classify- helps to categorize the input heart images. We have to pursue as "classify image using GoogleNet" and also swap with VGG-19.
- Train the network again and again to perform classification of images. For that we have to use "Train DL network to classify new images"
- Net- The network model trained on ImageNet datas or images
- Protocol used in this Net is "Net=VGG19"
- Layers- To specify the layers of deep learning based CNN used in VGG-19 network model.

The layer name along with total number o layers used in VGG-19 model is described in table 1.

Table 1. Description of layers used in VGG-19 model along with its description

Layer Name	**Number of layers**
Layers of convolutional neural networks	16
Layer that is completely interconnected	3
Max Pool layer	5
Layer of Softmax	1

c. Xception model (Model C)

The Xception model is inspired by Google's inception scheme and is based on the Extreme inception concept. The effortless along with its modular framework of Xception model is depicted in figure 3. This framework has linear stack of distance downward wise (depth) detachable convolution layers along with outstanding connections and spatial convolution which are non dependent in consecutive phases.

- Spatial convolution-Every channel has 3*3 convolutions
- Distance downward (depth) wise convolution- Every concatenation channels have 1*1 convolution.

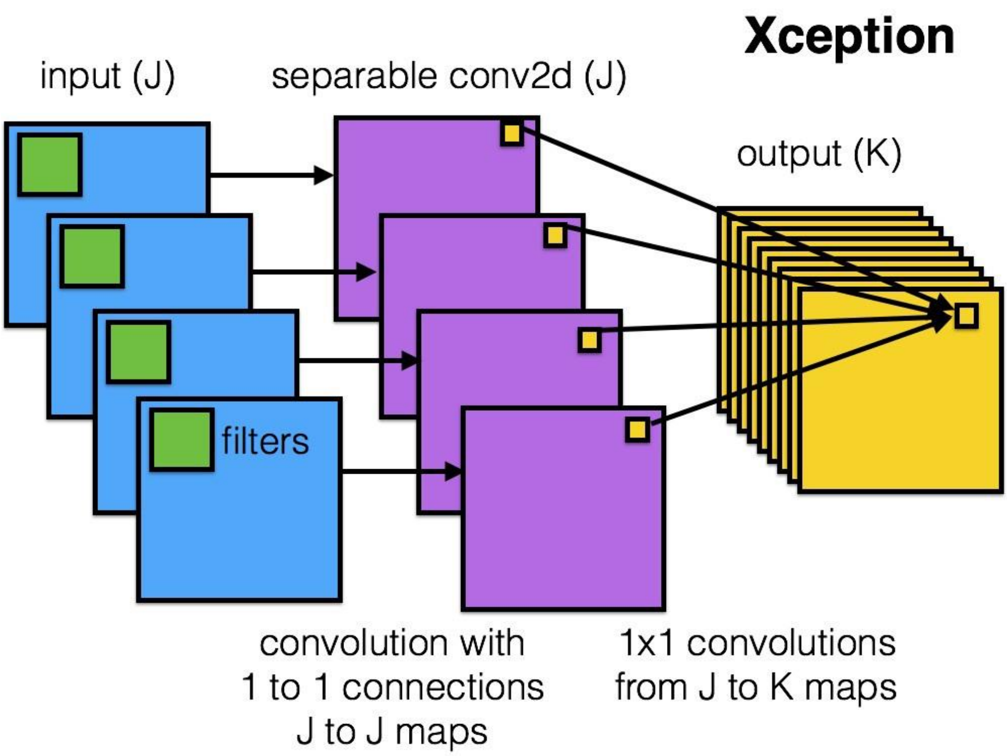

Figure 3. The architecture of Xception model

The number of features in this deep learning model is much reduced, which increases the competent intricacy. Furthermore, the cross-channel characteristics are maintained by this model. For example, consider a (3x3) Convolutional layer with 16 input channels and 32 output channels, resulting in a total convolution of (16x32x3x3)=4608 features. Also, the depth wise convolution is described as (16×3×3+16×32×1×1) has 656 features.

d. DenseNet 201

Every layer in this network receives additional provided images from previous layers and passes on its individual feature mappings to subsequent layers. Every layer in the network model receives a "shared acquaintance" from the layers before it. Figure 4 depicts the DenseNet201 network design.

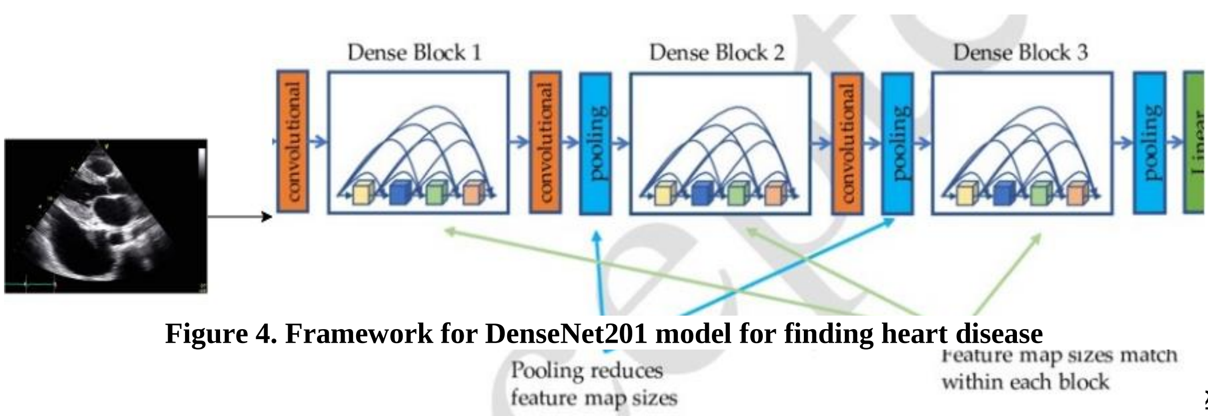

Figure 4. Framework for DenseNet201 model for finding heart disease

Because every layer receives feature maps from the preceding layer, the network may be thinner and compressed, resulting in a smaller number of channels. As a result, this model has stronger computational and memory abilities. Keras is a library for quickly implementing deep learning models with DenseNet201. The implementation of DenseNet201 model using Keras library are described below.

```
tf. keras.applications.DenseNet201(
    include_top=True, weights='imagenet', input_tensor=None,
    input_shape=None, pooling=None, classes=1000
)
```

This CNN model provides a variety of advantages, including parameter reclamation and a reduction in the number of parameters.

4. Metrics evaluation

The evaluation metrics are utilized to calculate the excellence of neural network models. Also, these metrics helps to validate the outcome of deep learning-based model which comprises of classification accuracy, loss and also confusion matrix.

***4.1 Accuracy*:**The number of correctly classified images from the total number of input heart mammography images is described as accuracy, which improves the performance of the Neural Network model in predicting heart disease diagnosis. The protocol utilized to compute accuracy is exposed in equation (1).

$$\text{Accuracy}=\frac{\text{Number of correctly classified heart images}}{\text{Total number of sample input heart images}} \tag{1}$$

***4.2 Precision*-** The proportion of correctly diagnosed Positive samples (Cardiac Amyloidosis) to the total number of Positive samples is used to calculate precision (either appropriately or inaccurately). Precision increases when the deep learning models have numerous accurate classification and smaller quantity inaccurate of classification. The value of precision is estimated using equation (2)

"The precision indicates how accurate the model is at categorizing Positive samples."

$$\text{Precision}= \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

***4.3Recall*-** Recall is the percentage of appropriate documents that are effectively recovered in retrieving information. Recall is measured using equation (3)

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

***4.4. F1-score*-** The harmonic mean of both precision and recall is defined by the F1 score, which is one of the accuracy measure metrics. Also this metric evaluate the binary classification model. Here we estimate this metric to distinguish the CA images and normal images. F-score can be calculated using equation(4)

$$\text{F} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The metrics such as precision, recall, F1-score and accuracy evaluation on several deep learning-based classification algorithm is illustrated in table2.

Table 2. Estimation of precision, recall, F1 score and accuracy for pre-trained models

Classification algorithm	Precision	Recall	F1-score	Accuracy

VGG-16	**0.88**	1.00	**0.93**	0.92
VGG-19	0.75	1.00	0.86	0.88
Xception model	0.86	1.00	0.92	**0.93**
DenseNet201	0.50	1.00	0.67	0.57

From the above table, we analyze that precision reaches highest scores of 88% using VGG-16, recall metrics produces 100% for all classification algorithm in CA disease prediction. Moreover, VGG-19 model achieves greater F1-score in disease prediction and Xception model attains maximum accuracy of 93% in CA disease identification along with its classification.

5. Experimental Analysis and outcomes

5.1 Effect on VGG-16

Figure 5 demonstrates that we trained deep based neural network model up to 25 epochs for identifying the Cardiac Amyloidosis infection in heart disease and undergoes classification by estimating accuracy, loss, validation accuracy and validation loss for VGG-16 model. In this network model, we reach maximum accuracy of 92% during 24th epochs and validation accuracy as 91.6% with less loss.

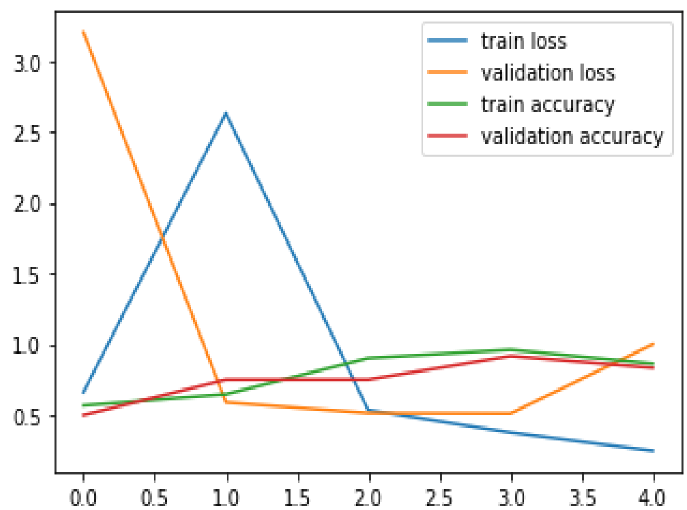

Figure 5. Accuracy and loss using VGG-16 model

5.2 Effect on VGG-19

We trained VGG-19 network model till 10 epochs for detecting heart based cardiac Amyloidosis disease via patient's heart MRI images and perform classification among heart images via calculating metrics such as accuracy and loss on both training and validation images. In this work, VGG-19 model attains an accuracy of 85.71% in predicting CA disease depicted in figure 6.

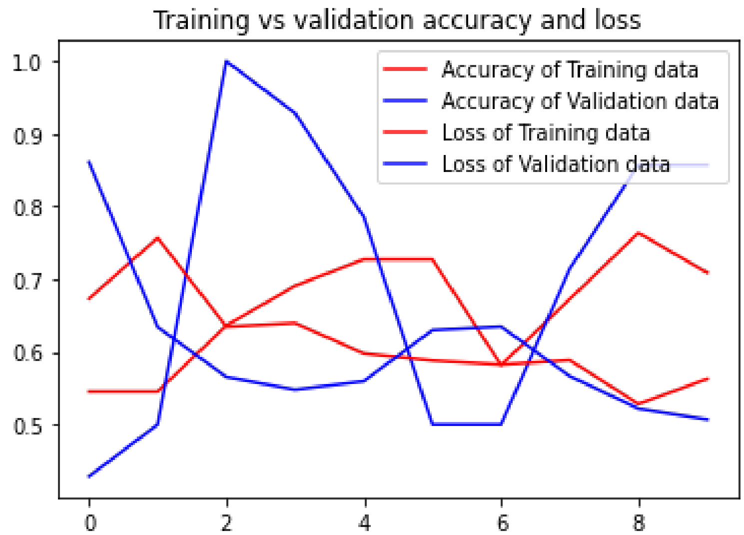

Figure 6. Accuracy and loss using VGG-19 model

5.3 Effect on Xception model

The effect of Xception model is to train the network model based on number of epochs to find cardiac Amyloidosis disease from heart images. Here, we predicted the disease by means of evaluating accuracy and loss during training phase and validation phase too. This model reaches an accuracy of 67.27% in heart disease diagnosis which is shown in figure 7.

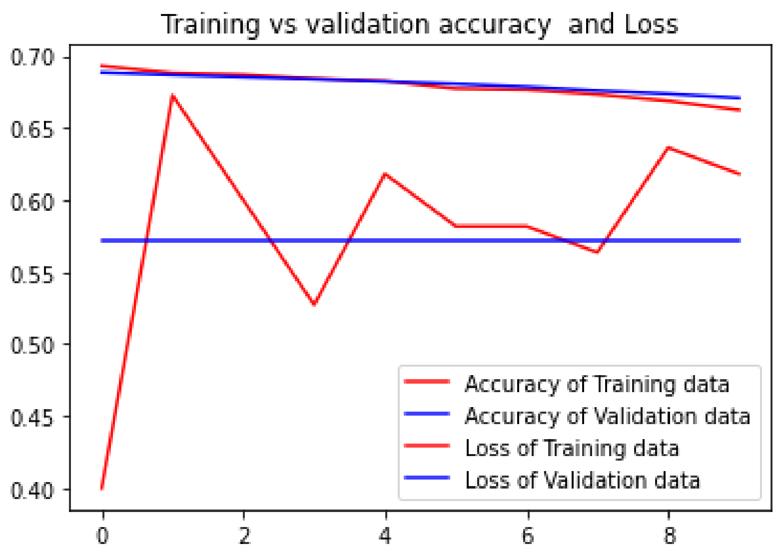

Figure 7. Xception network model accuracy and loss during training and validation

5.4 Effect on DenseNet 201 model

The effect of Xception model is to train the network model based on number of epochs to find cardiac Amyloidosis disease from heart images and perform classification of normal from abnormal images to predict heart disease. Here, we predicted the disease by means of evaluating accuracy and loss during training phase and validation phase too. This model reaches an accuracy of 92.86% shown in figure 8 in heart disease diagnosis.

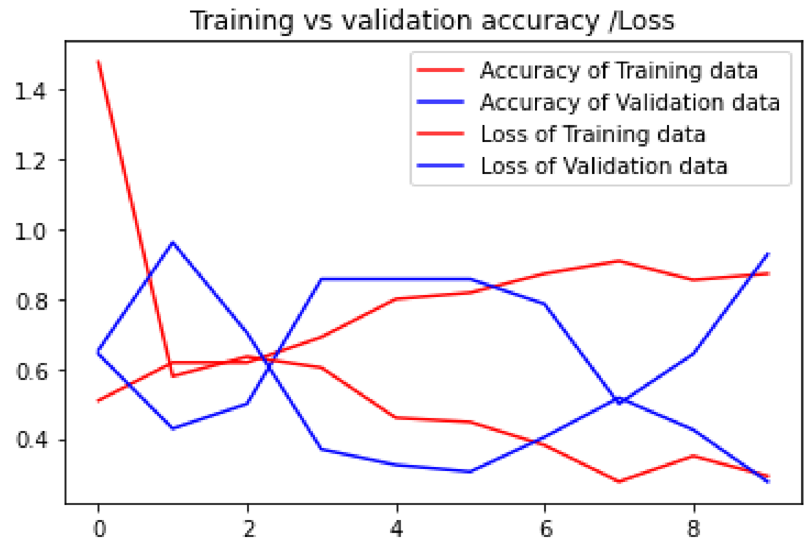

Figure 8. Accuracy and loss during training and validation using DenseNet 201 network model

6. Accuracy comparison for transfer learning based pre-trained model

Now, we are discussing deep learning based neural network models which help to train the input images. Moreover, the accuracy metrics is compared among all models for evaluating how the models performed in predicting CA disease. Among four models, DenseNet 201 model achieves highest accuracy of 92.86% in detecting disease from MRI images illustrated in table 3.

Table 3. Accuracy prediction for deep based pre-trained model

Pre-trained model	**Accuracy**
VGG-16	86.24
VGG-19	85.71
Xception model	67.27
DenseNet201	**92.86**

6.1 Macro average and Weighted Average

Here, we are describing how to evaluate scoring metrics (precision, recall, and f1-score) for multi-class classification issues using micro-averaging and macro-averaging schemes. For a multi-class classification task, weighted accuracy, recall, and f1-score metrics are compared to micro-average and macro-average scoring metrics are shown in table 4.

Table 4. Classification of heart MRI images by metrics evaluation

Classification algorithm	**Macro average**			**Weighted average**		
	Precision	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**
VGG-16	**0.94**	0.90	0.91	0.93	0.92	0.91
VGG-19	0.88	0.88	0.86	0.89	0.86	0.86
DenseNet201	0.93	**0.94**	**0.93**	**0.94**	**0.93**	**0.93**
Xception model	0.75	0.62	0.53	0.79	0.57	0.51

7. Conclusion

In this paper, we conclude that deep based neural network models such as VGG-16, VGG-19, Xception model and DenseNet model are trained to predict the affected region on heart MRI images. Moreover, comparative analysis has performed for finding which model generateseffective improvement in predicting cardiac Amyloidosis disease via images. For evaluating the performance of the model, several metrics such as precision, recall, F1-score using both micro average and macro average. Among all trained models, DenseNet201 model achieved maximum accuracy 92.86% for detecting heart disease especially Cardiac Amyloidosis disease.

References

[1] Agibetov, A., Seirer, B., Dachs, T. M., Koschutnik, M., Dalos, D., Rettl, R., ... & Bonderman, D. (2020). Machine learning enables prediction of cardiac amyloidosis by routine laboratory parameters: a proof-of-concept study. Journal of clinical medicine, 9(5), 1334.

[2] Mehmood, A., Iqbal, M., Mehmood, Z., Irtaza, A., Nawaz, M., Nazir, T., & Masood, M. (2021). Prediction of Heart Disease Using Deep Convolutional Neural Networks. Arabian Journal for Science and Engineering, 46(4), 3409-3422.

[3] Duca, F., Kammerlander, A. A., Panzenböck, A., Binder, C., Aschauer, S., Loewe, C., ... &Mascherbauer, J. (2018). Cardiac magnetic resonance T1 mapping in cardiac amyloidosis. JACC: Cardiovascular Imaging, 11(12), 1924-1926.

[4] Narmadha, S., Gokulan, S., Pavithra, M., Rajmohan, R., &Ananthkumar, T. (2020, July). Determination of various Deep Learning Parameters to Predict Heart Disease for Diabetes Patients. In 2020 International Conference on System, Computation, Automation and Networking (ICSCAN) (pp. 1-6). IEEE.

[5] Gertz, M. A. (2018). Immunoglobulin light chain amyloidosis diagnosis and treatment algorithm 2018. Blood cancer journal, 8(5), 1-8.

[6] Ghorbani, A., Ouyang, D., Abid, A., He, B., Chen, J. H., Harrington, R. A., ... & Zou, J. Y. (2020). Deep learning interpretation of echocardiograms. NPJ digital medicine, 3(1), 1-10.

[7] Huda, A., Castaño, A., Niyogi, A., Schumacher, J., Stewart, M., Bruno, M., ... & Shah, S. J. (2021). A machine learning model for identifying patients at risk for wild-type transthyretin amyloid cardiomyopathy. Nature communications, 12(1), 1-12.

[8] Gárate-Escamila, A. K., El Hassani, A. H., &Andrès, E. (2020). Classification models for heart disease prediction using feature selection and PCA. *Informatics in Medicine Unlocked*, *19*, 100330.

[9] Kittleson, M. M., Maurer, M. S., Ambardekar, A. V., Bullock-Palmer, R. P., Chang, P. P., Eisen, H. J., ... & American Heart Association Heart Failure and Transplantation Committee of the Council on Clinical Cardiology. (2020). Cardiac amyloidosis: evolving diagnosis and management: a scientific statement from the American Heart Association. *Circulation*, *142*(1), e7-e22.

[10] Li, W., Lazarus, A., Gao, H., Martinez-Naharro, A., Fontana, M., Hawkins, P., ... & Luo, X. (2020). Analysis of cardiac amyloidosis progression using model-based markers. *Frontiers in physiology*, *11*, 324.

[11] Brunese, L., Martinelli, F., Mercaldo, F., &Santone, A. (2020). Deep learning for heart disease detection through cardiac sounds. *Procedia Computer Science*, *176*, 2202-2211.

[12] Asmare, M. H., Woldehanna, F., Janssens, L., &Vanrumste, B. (2020, July). Rheumatic Heart Disease Detection Using Deep Learning from Spectro-Temporal Representation of Un-segmented Heart Sounds. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 168-171). IEEE.

[13] Martini, N., Aimo, A., Barison, A., Della Latta, D., Vergaro, G., Aquaro, G. D., ... &Chiappino, D. (2020). Deep learning to diagnose cardiac amyloidosis from cardiovascular magnetic resonance. *Journal of Cardiovascular Magnetic Resonance*, *22*(1), 1-11.

[14] McVeigh, T., & Tennyson, C. (2020). Understanding and recognizing cardiac amyloidosis. *Journal of the American Academy of PAs*, *33*(10), 16-20.

[15] Muhammad, Y., Tahir, M., Hayat, M., & Chong, K. T. (2020). Early and accurate detection and diagnosis of heart disease using intelligent computational model. *Scientific reports*, *10*(1), 1-17.

[16] Gokulan, S., Narmadha, S., Pavithra, M., Rajmohan, R., &Ananthkumar, T. (2020, July). Determination of Various Deep Learning Parameter for Sleep Disorder. In *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)* (pp. 1-6). IEEE.

[17] Satriano, A., Afzal, Y., Afzal, M. S., Hassanabad, A. F., Wu, C., Dykstra, S., ... & White, J. A. (2020). Neural-Network-Based Diagnosis Using 3-Dimensional Myocardial Architecture and Deformation: Demonstration for the Differentiation of Hypertrophic Cardiomyopathy. *Frontiers in Cardiovascular Medicine*, *7*.

[18] Nitsche, C., Scully, P. R., Patel, K. P., Kammerlander, A. A., Koschutnik, M., Dona, C., ... &Treibel, T. A. (2021). Prevalence and outcomes of concomitant aortic stenosis and cardiac amyloidosis. *Journal of the American College of Cardiology*, *77*(2), 128-139.

[19] Selvi, S. A., Kumar, T. A., & Rajesh, R. S. (2021). CCNN: A Deep Learning Approach for an Acute Neurocutaneous Syndrome via Cloud-Based MRI Images. In Handbook of Deep Learning in Biomedical Engineering and Health Informatics (pp. 83-102). Apple Academic Press.

[20] Zheng, Y., Yang, C., &Merkulov, A. (2018, May). Breast cancer screening using convolutional neural network and follow-up digital mammography. In *Computational Imaging III* (Vol. 10669, p. 1066905). International Society for Optics and Photonics.

[21] Narmadha, S., Gokulan, S., Pavithra, M., Rajmohan, R., &Ananthkumar, T. (2020, July). Determination of various Deep Learning Parameters to Predict Heart Disease for Diabetes Patients. In 2020 International Conference on System, Computation, Automation and Networking (ICSCAN) (pp. 1-6). IEEE.

[22] Jeyaranjani, J., Rajkumar, T. D., & Kumar, T. A. (2021). Coronary heart disease diagnosis using the efficient ANN model. Materials Today: Proceedings.

[23] Sengan, S., Kamalam, G. K., Vellingiri, J., Gopal, J., Velayutham, P., &Subramaniyaswamy, V. (2020). Medical information retrieval systems for e-Health care records using fuzzy based machine learning model. Microprocessors and Microsystems, 103344.

[24] Sengan, S., Arokia Jesu Prabhu, L., Ramachandran, V., Priya, V., Ravi, L., &Subramaniyaswamy, V. (2020). Images super-resolution by optimal deep AlexNet architecture for medical application: a novel DOCALN. Journal of Intelligent & Fuzzy Systems, (Preprint), 1-14.