Cardiomegaly Detection from Chest X-Rays using CNN, Transfer Learning with Attention Algorithm

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***Abstract*—Cardiomegaly is a condition where the heart is enlarged beyond its normal size due to various factors. The patient's ability to receive effective treatment depends on the early identification of cardiomegaly. For the categorization of cardiomegaly in chest X-ray images, we proposed a comparative analysis of four different deep-learning models in this paper. For the objective of cardiomegaly detection from chest X-rays, we evaluated the results of ResNet50, InceptionV3, DenseNet121, and EfficientNetB0 on balanced and unbalanced datasets. In the validation set, MobileNetV1 obtained the maximum accuracy of 0.7968, while in the test set, it achieved the best accuracy of 0.781. In the unbalanced dataset, MobileNetV1 achieved the highest accuracy of 0.8458 in the validation set and 0.8386 in the test set. The outcomes also demonstrate that the performance of the models varied considerably according to how the rest of the dataset was distributed.**

Keywords—Cardiomegaly, Chest X-Rays, Convolutional Neural Network, CNN, Transfer Learning, Deep Learning.

I. Introduction

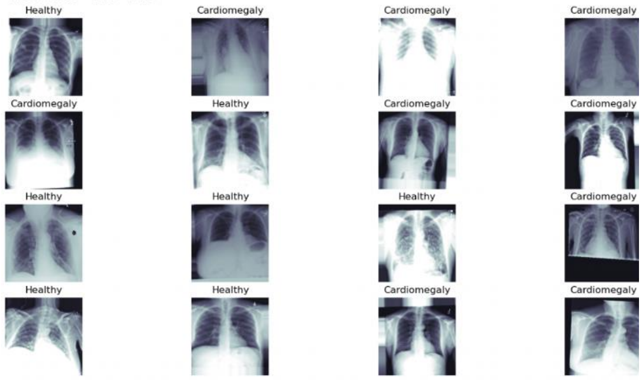
Cardiomegaly is a condition characterised by an enlarged heart, usually caused by underlying heart disease or other health conditions. The enlargement of the heart can lead to decreased pumping efficiency, which can result in a variety of symptoms such as shortness of breath, chest pain, and fatigue. In severe cases, cardiomegaly can lead to heart failure, arrhythmias, and even sudden cardiac death.

Cardiomegaly isn’t a disease itself but is rather a change in the heart muscle as a result of an underlying heart condition. These conditions either make the heart work harder to pump blood throughout the body or damage the heart muscle, so the heart enlarges to compensate for the extra exertion. Coronary artery disease, high blood pressure, cardiomyopathy, pulmonary hypertension, pericarditis, anaemia, thyroid disease, hemochromatosis, heart valve disease, congenital heart conditions, pregnancy, and a family history of cardiomegaly can all lead to the development of cardiomegaly. Shortness of breath, irregular heartbeats, exhaustion, chest pain, and swollen feet are common signs or symptoms of an enlarged heart.

Having this illness can be extremely risky because it raises the likelihood of sudden cardiac arrest and heart failure. Considering that heart disease is the leading cause of death in the United States [1] and that the majority of mild cardiomegaly cases present with no symptoms, it can make a significant difference to be able to automatically identify this condition in the analysis of chest x-rays. [2] However, accurately detecting cardiomegaly from chest X-rays can be challenging, even for experienced radiologists.

Chest X-rays are most commonly used for the diagnosis of heart and chest-related pathologies. In recent years, research on computer-aided pathology diagnosis from chest X-rays has advanced rapidly, leading to the creation of a sizable corpus of open-source X-ray data combined with ground truths and the creation of numerous intricate deep-learning algorithms. [2] These models have shown promise in accurately detecting cardiomegaly from chest X-rays, but there is still room for improvement. In this project, we aim to contribute to this area by performing a comparative analysis of four different deep learning models: Efficient Net B4, InceptionV3, MobileNetV1, and ResNet152-V2. Our contribution is a comparative analysis of these models, which can provide valuable insights for medical practitioners and researchers in the field of cardiology. By identifying which models perform best at detecting cardiomegaly from chest X-rays, we can help to improve the accuracy of diagnostic tools for this condition. This, in turn, can lead to earlier detection and treatment, and ultimately better outcomes for patients. Fig 1 shows the labelled chest X-ray images dataset that we have used in the project to perform image classification.

The rest of the paper is organized as follows. Section II provides a review of previous research on detecting Cardiomegaly using deep learning models. Section III introduces the proposed model and describes the implementation. The evaluation results and experimental validation are shown in Section IV. Finally, in Section V, we conclude this paper and address future research.



II. Literature Review

According to some of the most recent research articles on the topic, deep learning approaches are increasingly being used to identify cardiomegaly. These researches show how well convolutional neural network-based computer-aided diagnostic systems can identify cardiomegaly in a variety of imaging modalities, including CT (Computed Tomography), MRI (Magnetic resonance imaging), ECG (ElectroCardiogram), and chest X-ray pictures.

The authors of [2] proposed an automated technique that uses a U-Net-based architecture to separate the heart and lungs from a chest X-ray and then calculate the cardiothoracic ratio to evaluate whether or not cardiomegaly is present. The overall choice made by the deep learning model is understandable thanks to the segmentation outputs for the lung and heart regions and the automatic CTR calculation.

The authors of [3] proposed a diagnosis support model of cardiomegaly based on CNN using ResNet and an explainable feature map. To configure the model, initially, a cardiomegaly diagnosis model is configured using ResNet, and a chest X-ray data set is used and learned. Through the proposed model, the authors claimed that the diagnosis of cardiomegaly using CNN and chest X-ray imaging is low-priced, highly accessible, and provides highly accurate results through AI algorithms. Additionally, they claimed that a very successful support system might be created in the event that disease judgement standards applicable to conditions like cardiomegaly are proven through the explainable feature map to be consistent with the organ position and form indicated on the X-ray image.

In the paper [4] by Sarpotdar, S. S., 2022, the authors used a deep learning-based customized retrained U-Net model to detect cardiomegaly from chest X-rays. The author found high accuracy and sensitivity results and came to the conclusion that the U-Net design has the potential to increase the accuracy and efficiency of the diagnostic procedure for cardiomegaly, resulting in better patient outcomes. To reduce computing time, the authors made this model perform data preprocessing, picture improvement, image compression, and classification before moving on to the training step. The work used a chest x-ray image dataset to simulate and produced a high diagnostic accuracy.

The authors of [5] proposed two pre-trained convolutional neural networks (CNNs) shuffle and mobile net, to detect two types of abnormalities, namely atelectasis and cardiomegaly. The authors observed that both models have high accuracy in terms of detecting the disease correctly. The authors felt that their work can be improved using a huge dataset besides exploiting other types of pre-trained networks to extract more relevant features and perform higher accuracy for many types of diseases.

All the research papers, discussed here show how well convolutional neural network-based computer-aided diagnostic systems can identify cardiomegaly with the help of chest X-rays. With the continued advancement of deep learning techniques and the availability of large-scale annotated datasets, these models have the potential to assist radiologists and physicians in the accurate and efficient diagnosis of cardiomegaly.

III. Project Details and Methodology

A. *Definitions*

Cardiomegaly is a medical condition where the heart is enlarged beyond its normal size. It can be caused by a variety of factors, including high blood pressure, heart disease, and other underlying medical conditions.

A chest X-ray is a medical imaging test that uses low-dose radiation to create images of the chest, including the lungs, heart, and other organs.

CNN stands for Convolutional Neural Network, which is a type of deep learning algorithm commonly used for image recognition tasks. CNNs are designed to automatically extract features from images and learn to recognize patterns in the data.

Transfer learning is a machine learning technique where a pre-trained model is used as a starting point for training a new model on a specific task. By leveraging the knowledge learned by the pre-trained model, transfer learning can enable faster and more efficient training of new models.

Binary classification is a type of machine learning task where the goal is to classify inputs into one of two categories. In the context of this project, the goal is to classify chest X-ray images as either containing evidence of cardiomegaly or not containing evidence of cardiomegaly.

B. *Specifications*

- Problem statement: The project aims to develop a deep learning approach to automatically detect cardiomegaly from chest X-rays using CNNs and transfer learning.

- Inputs: The input to the model will be a chest X-ray image in digital format. The model should be able to handle different image sizes and resolutions.

- Outputs: The output of the model will be a binary classification indicating whether or not the input image contains evidence of cardiomegaly.

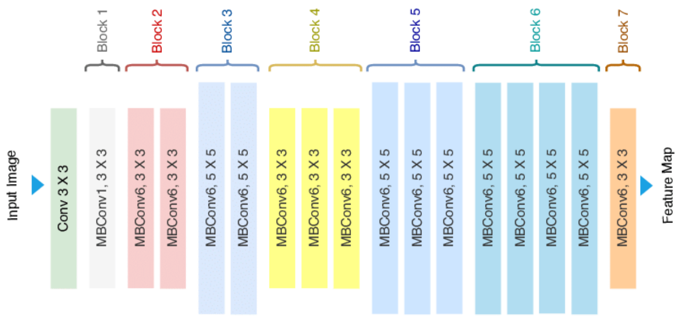
- Dataset: The project will use a publicly available dataset of chest X-rays, such as the NIH (National Institutes of Health) dataset. The dataset contained images from many classes such as Pneumonia, Emphysema and Cardiomegaly. The dataset was first processed to characterize images marked as Cardiomegaly and all other images as non-Cardiomegaly. Then, The images in the dataset will be preprocessed by resizing them to a fixed size and normalizing the pixel values. The data will be split into training, validation, and testing sets. The dataset should contain a sufficient number of images with cardiomegaly and without cardiomegaly.

- Data preprocessing: The images in the dataset will be preprocessed by resizing them to a fixed size and normalizing the pixel values. The data will be split into training, validation, and testing sets.
- Model architecture: We employ the method of using convolutional neural network (CNN) with an attention mechanism. The model employs transfer learning, utilizing pre-trained weights from popular image classification models such as EfficientNetB4, InceptionV3, MobileNetV1, and ResNet152V2. The architecture includes global weighted average pooling, dropout, and two fully connected layers for classification. The attention mechanism allows the model to selectively focus on regions of interest in the input image, improving its ability to detect features relevant to cardiomegaly. The model is trained on a balanced dataset to ensure that the performance metrics are not biased towards specific class. The performance of the model is evaluated using various metrics such as accuracy, sensitivity, specificity, precision, and F1 score.
- Hyperparameters: The hyperparameters for the model, such as the learning rate and batch size, will be chosen through experimentation and validation.
- Evaluation metrics: The model will be evaluated using different evaluation metrics such as accuracy, sensitivity, specificity, positive predictive value, negative predictive value and F-score. The evaluation will be performed on the validation and testing set.
- Implementation: The project will be implemented using Python and the TensorFlow deep learning framework. A GPU will be used to accelerate the computation.
- Performance requirements: The model should be able to achieve a high level of accuracy and sensitivity in detecting cardiomegaly from chest X-rays. The model should be able to handle a large number of images efficiently.
- Deliverables: The project will deliver a trained model that can automatically detect cardiomegaly from chest X-rays, along with the source code and documentation for the implementation.

C. *Architecture*

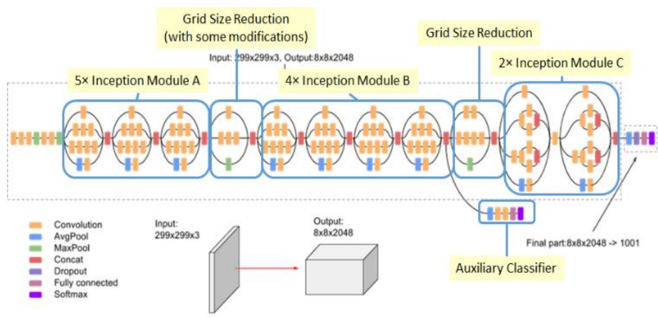
EfficientNet-B4:

EfficientNet B4 is a convolutional neural network architecture that was introduced by Tan et al. in their paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" in 2019. It is part of a family of EfficientNet models (B0 to B7) that are designed to achieve state-of-the-art performance on image classification tasks while maintaining efficiency in terms of computational resources and model size. The EfficientNet B4 architecture has a depth of 23 layers and a total of 19M parameters. The model is composed of a series of convolutional layers, followed by batch normalization and ReLU activation. The core of the model is a series of blocks that are repeated multiple times, each block consisting of a combination of convolutional layers, batch normalization, and a non-linear activation function. One key innovation of EfficientNet B4 is the use of a compound scaling method, which involves scaling the depth, width, and resolution of the network simultaneously. This method enables the network to efficiently learn features at different scales, improving its ability to handle a wide range of image sizes and variations.



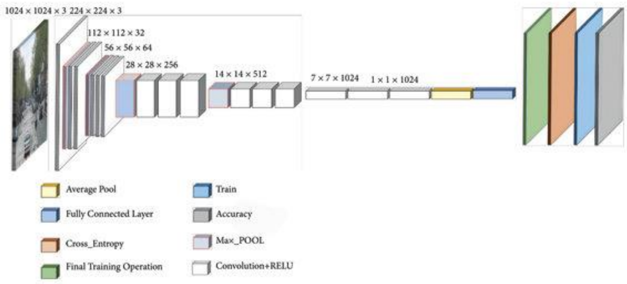
Inception – V3:

Inception-v3 is a convolutional neural network architecture that was introduced by Szegedy et al. in their paper "Rethinking the Inception Architecture for Computer Vision" in 2015. It is an improved version of the earlier Inception-v1 and Inception-v2 models, designed to achieve better accuracy on image classification tasks while maintaining efficiency in terms of computational resources and model size. The Inception-v3 architecture is composed of multiple convolutional layers, followed by pooling, batch normalization, and a non-linear activation function. The core of the model is a series of "Inception modules", which are blocks that are repeated multiple times, each consisting of a set of parallel convolutional layers with different kernel sizes, followed by pooling and concatenation of their outputs. One key innovation of Inception-v3 is the use of "factorized" convolutions, which are separable convolutions that are decomposed into a depthwise convolution and a pointwise convolution. This reduces the number of parameters in the model, making it more efficient and easier to train.



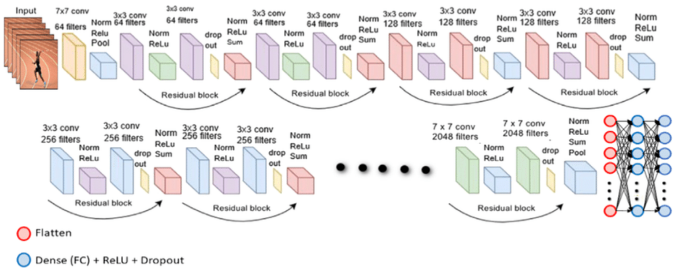
MobileNet-V1:

MobileNet V1 is a convolutional neural network architecture that was introduced by Howard et al. in their paper "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications" in 2017. It is specifically designed for mobile and embedded devices, with the goal of achieving high accuracy on image classification tasks while minimizing the computational resources and model size required. The MobileNet V1 architecture is composed of a series of depthwise separable convolutions, which are a combination of depthwise convolutions and pointwise convolutions. Depthwise convolutions apply a single convolutional filter per input channel, while pointwise convolutions apply 1x1 filters to mix the output channels from the depthwise convolution. This approach significantly reduces the number of parameters and computational resources required by the model, while still capturing important features in the input image. MobileNet V1 also uses a technique called "linear bottleneck", which involves using a 1x1 convolution to reduce the dimensionality of the input before applying the depthwise separable convolution. This further reduces the number of parameters and computational resources required by the model.



ResNet152 – V2:

ResNet152v2 is a convolutional neural network architecture that was introduced by He et al. in their paper "Deep Residual Learning for Image Recognition" in 2016. It is an extension of the original ResNet architecture, designed to achieve even better performance on image classification tasks by improving the residual connections and incorporating additional network layers. The ResNet152v2 architecture is composed of a series of convolutional layers, followed by pooling, batch normalization, and a non-linear activation function. The core of the model is a series of "residual blocks", which are composed of two or more convolutional layers with skip connections that bypass the intermediate layers. One key innovation of ResNet152v2 is the use of "bottleneck" blocks, which are a form of "depthwise bottleneck" block that uses 1x1 convolutions to reduce the dimensionality of the input before applying the main 3x3 convolution. This reduces the computational cost of the model while improving its accuracy.



D. Platform

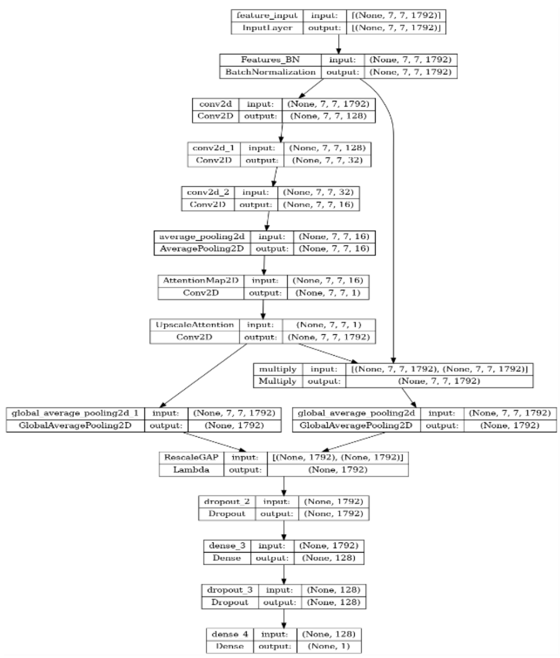
The proposed method has been implemented using Python, Keras, TensorFlow and Deep Learning frameworks. We used GPU for training and testing our models to accelerate the computations.

E. Design

Implementation involved customizing four state-of-the-art convolutional neural network models: EfficientNet B4, Inception V3, MobileNet V1, and ResNet152 V2. To improve the performance of these models, we added an attention mechanism that enables the models to focus on relevant features while ignoring irrelevant ones.

We also incorporated a global weighted average pooling layer that allows the models to learn more informative features from the input data. The output of the models was passed through a classification layer with dropout and two fully connected layers to generate the final prediction of the presence or absence of cardiomegaly in chest X-rays.

By customizing these pre-trained models with attention and pooling layers, we were able to improve their performance in detecting cardiomegaly, achieving high accuracy, sensitivity, specificity, precision, and F1 score.



Customized Pretrained Model Input with Attention Model

IV. Experimental Setup

A. Implementation Details

The implementation of our Cardiomegaly Detection system was done using the Keras deep learning framework with a TensorFlow backend. We used Python as our programming language. We used the publicly available NIH(National Institute of Health) Chest X-ray dataset, which consists of 112,120 frontal-view chest X-ray images from 30,805 unique patients, labeled with 14 different thoracic diseases, including cardiomegaly. We preprocessed the images by resizing them to 224x224 pixels and normalizing the pixel values to a range of [0,1]. We first organized the ChestX-ray14 dataset into two categories: one for cases with cardiomegaly and one for cases without cardiomegaly. We then performed exploratory data analysis techniques to examine the distributions and check the balance of the dataset.

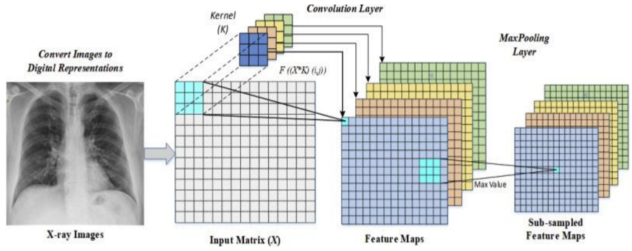
We split the dataset into training, validation, and test datasets with a ratio of 80:08:12. To balance the distribution in the dataset, we used oversampling to increase the number of cases with cardiomegaly by data augmentation. We used the ImageDataGenerator function in Keras to perform data augmentation on the training dataset, including horizontal and vertical flipping, random rotation, and zooming.

The implementation of the dataset on the entire model without any pretrained weights, as well as on the model with an appended layer of fully connected layers, did not give satisfactory accuracy. This approach was tried initially to train the model from scratch without any prior knowledge or weights. However, due to the lack of training data and the complexity of the problem, the accuracy obtained was not up to the mark. Hence, the transfer learning approach was utilized, where a pre-trained model was used as a starting point for training the model on the given dataset. Although the accuracy improved significantly, the performance was still not optimal.

Therefore, we added an attention model to the pre-trained models to improve their performance. We also applied global weighted average pooling to capture the most important features of the images and output them to a classification layer with dropout and two fully connected layers.

We also applied these techniques on both unbalanced and balanced datasets. Using an unbalanced dataset can be problematic because it can lead to biased and inaccurate model performance. In an unbalanced dataset, the number of examples in each class is not evenly distributed. This means that the model is more likely to be trained on one class over another, which can result in a biased model that performs poorly on the underrepresented class. On the other hand, a balanced dataset ensures that the model is trained on an equal number of examples from each class, resulting in a more accurate and unbiased model. The model is forced to learn the features that are common to all classes rather than relying on the bias towards one class.

We trained the models using transfer learning, fine-tuning pre-trained models on the ImageNet dataset, including Efficient Net B4, InceptionV3, MobileNetV1, and ResNet152-V2. We initialized the models with their pre-trained weights and then trained them on the balanced NIH dataset with the added attention model and global weighted average pooling. We used the binary cross-entropy loss function and the Adam optimizer with a learning rate of 1e-3. We used early stopping with patience of 10 to prevent overfitting.



$$\mathrm{GWAP}(x,y,d) = \frac{\sum_x \sum_y \mathrm{Attention}(x,y,d)\mathrm{Feature}(x,y,d)}{\sum_x \sum_y \mathrm{Attention}(x,y,d)}$$

Global Weighted Average

B. Testing

To evaluate the performance of our "Cardiomegaly Detection from Chest X-Rays using CNN and Transfer Learning Algorithm" implementation, we tested our models on the previously split test dataset. We used a confusion matrix to visualize the performance of our models in predicting true positive, false positive, true negative, and false negative cases.

We also calculated the accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and F1 score for each model. Our results indicate that the proposed approach is effective in detecting cardiomegaly from chest X-rays. However, there is still room for improvement, and future work can focus on addressing the imbalanced nature of the dataset and exploring other deep-learning models to further enhance the performance of the system.

TP = True Positive	*TN = True Negative*
FP = False Positive	*FN = False Negative*

Accuracy = (TP+TN)/(TP+FP+FN+TN)
Sensitivity/Recall = TP/(TP+FN)
Specificity = TN/(TN+FP)
Positive Predictive Value = TP/(TP+FP)
Negative Predictive Value = TN/(TN+FN)
F1 Score = 2(Recall * Precision) / (Recall + Precision)*

C. Discussions on Finding and Challenges

TABLE I. Balanced dataset

Models	**Results (BALANCED DATASET)**		
	Metrics used to measure	***Validation***	***Test***
EfficientNetB4	Accuracy	0.7457	0.7349
	Positive Predictive Value	0.4187	0.4004

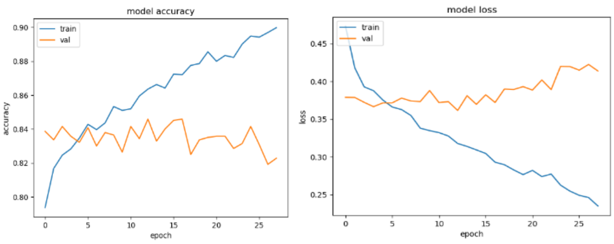
Models	Results (BALANCED DATASET)		
	Metrics used to measure	*Validation*	*Test*
	Negative Predictive Value	0.9083	0.8964
	Sensitivity	0.6942	0.6511
	Specificity	0.7586	0.7559
	F Score	0.77	0.76
InceptionV3	Accuracy	0.7579	0.7586
	Positive Predictive Value	0.4378	0.4376
	Negative Predictive Value	0.9197	0.9162
	Sensitivity	0.7338	0.7194
	Specificity	0.764	0.7685
	F Score	0.78	0.78
MobileNetV1	Accuracy	0.7968	0.781
	Positive Predictive Value	0.4945	0.4672
	Negative Predictive Value	0.9051	0.9062
	Sensitivity	0.6511	0.6655
	Sensitivity	0.8333	0.8099
	F Score	0.81	0.79
ResNet152V2	Accuracy	0.7767	0.7767
	Positive Predictive Value	0.4577	0.4581
	Negative Predictive Value	0.896	0.8976
	Sensitivity	0.6223	0.6295
	Sensitivity	0.8153	0.8135
	F Score	0.79	0.79

TABLE II. UN-BALANCED DATASET

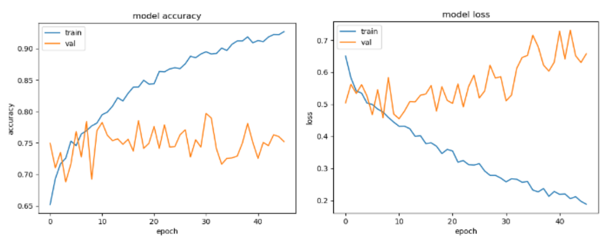
Models	Results (DATASET NOT BALANCED)		
	Metrics used to measure	*Validation*	*Test*
EfficientNetB4	Accuracy	0.8314	0.8184
	Positive Predictive Value	0.6429	0.5903
	Negative Predictive Value	0.8549	0.8449
	Sensitivity	0.3561	0.3058
	Specificity	0.9505	0.9468
	F Score	0.81	0.79
InceptionV3	Accuracy	0.8343	0.8249
	Positive Predictive Value	0.6463	0.6115
	Negative Predictive Value	0.8595	0.8522
	Sensitivity	0.3813	0.3453
	Specificity	0.9477	0.945
	F Score	0.82	0.81
MobileNetV1	Accuracy	0.8458	0.8386

Models	Results (DATASET NOT BALANCED)		
	Metrics used to measure	*Validation*	*Test*
	Positive Predictive Value	0.7133	0.6688
	Negative Predictive Value	0.8619	0.8607
	Sensitivity	0.3849	0.3849
	Sensitivity	0.9613	0.9523
	F Score	0.83	0.82
ResNet152V2	Accuracy	0.835	0.8401
	Positive Predictive Value	0.6899	0.6944
	Negative Predictive Value	0.8499	0.8569
	Sensitivity	0.3201	0.3597
	Sensitivity	0.964	0.9604
	F Score	0.81	0.82

The table shows the results of four different pre-trained models, EfficientNetB4, InceptionV3, MobileNetV1, and ResNet152V2, on both balanced and unbalanced datasets for the task of cardiomegaly detection from chest X-rays. The balanced dataset results reveal that MobileNetV1 achieved the highest accuracy of 0.7968 in the validation set and 0.781 in the test set, followed by InceptionV3 with 0.7579 in the validation set and 0.7586 in the test set. The unbalanced dataset results show that MobileNetV1 achieved the highest accuracy of 0.8458 in the validation set and 0.8386 in the test set, followed by ResNet152V2 with 0.835 in the validation set and 0.8401 in the test set. However, the sensitivity scores of all models were low for both balanced and unbalanced datasets, indicating that the models had difficulty in detecting true positives. The results also show that the performance of the models varied significantly depending on the balance of the dataset. The findings suggest that more efforts are needed.
to improve the sensitivity scores of the models for better cardiomegaly detection

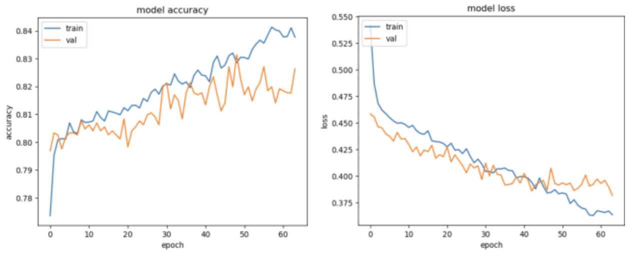


Mobile Net V1 Model Accuracy and Loss for Unbalanced
Dataset

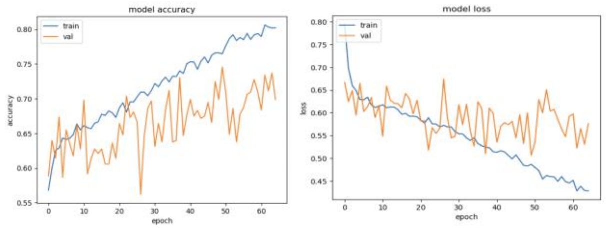


Mobile Net V1 Model Accuracy and Loss for Balanced

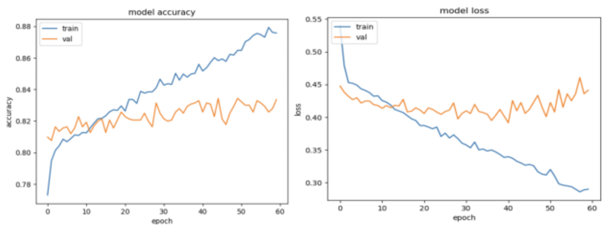
Dataset



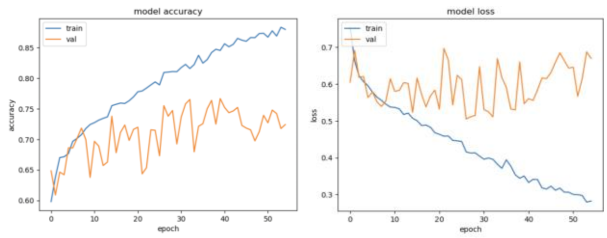
EfficientNetB4 Model Accuracy and Loss for Unbalanced Dataset



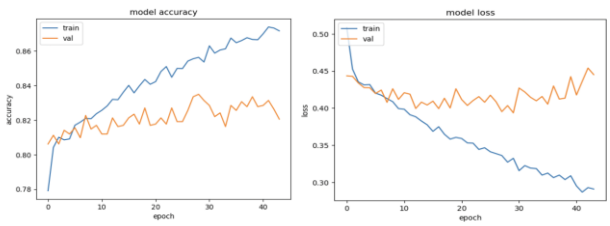
EfficientNetB4 Model Accuracy and Loss for Balanced Dataset



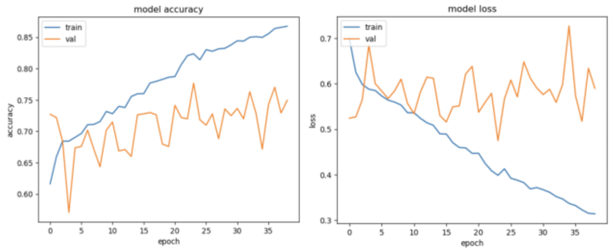
Inception V3 Model Accuracy and Loss for Unbalanced Dataset



Inception V3 Model Accuracy and Loss for Balanced Dataset



ResNet152V2 Model Accuracy and Loss for Unbalanced Dataset



ResNet152V2 Model Accuracy and Loss for Balanced Dataset

V. CONCLUSION AND FUTURE WORK

The paper presents a deep learning-based approach for the detection of cardiomegaly from chest X-rays using transfer learning algorithms. The proposed method involved preprocessing the NIH Chest X-ray dataset, splitting it into training, validation, and test datasets, oversampling to balance the distribution in the dataset, applying data augmentation, and using transfer learning. The models were trained on four pre-trained models, including EfficientNetB4, InceptionV3, MobileNetV1, and ResNet152V2, with the added attention model and global weighted average pooling. The results suggest that the proposed approach is effective in detecting cardiomegaly from chest X-rays. However, there is still room for improvement, and future work can focus on addressing the imbalanced nature of the dataset and exploring other deep-learning models to further enhance the performance of the system.

There are several potential future directions for this project. First, one could explore the use of larger and more diverse datasets for training the models, including data from multiple sources and modalities. This could improve the generalizability of the models and potentially lead to better performance on real-world data. Second, one could investigate the use of more advanced transfer learning techniques, such as fine-tuning the entire model or using more advanced pre-training methods. This could potentially lead to even better performance on the Cardiomegaly detection task. Finally, one could investigate the potential clinical impact of these models, for example by integrating them into clinical decision support systems or using them to guide treatment decisions. Overall, there is significant potential for future research in this area, and the development of more accurate and effective models for Cardiomegaly detection could have a positive impact on patient outcomes.

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