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APPLYING ARTIFICIAL INTELLIGENCE TECHNIQUES IN CARDIOMEGALY DETECTION USING CHEST X-RAYS

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ABSTRACT

The evolution of artificial intelligence in several areas has allowed machines or techniques to accomplish any task with high accuracy, like detecting and classifying chest X-rays as cardiomegaly or healthy. The goal of this paper is to develop a deep learning technique to identify and classify chest X-rays, whether the images are health-related or cardiomegaly. Firstly, the chest X-ray dataset is used that called ChestX-ray8, which contains medical images about many diseases, including cardiomegaly. After that, we apply the preprocessing steps to the dataset, like making all images the same size and normalizing them. Before applying the deep learning techniques, it should use data augmentation methods, such as random rotation, random zoom, and random brightness. The deep learning technique used is the VGG16, which is a convolutional neural network model. The results show that the VGG16 model gives a high accuracy of 91% compared with the previous works.
Keywords: *Artificial Intelligence, Cardiomegaly, Images, Chestx-Ray8, VGG16*

1. INTRODUCTION

Chest radiography is commonly employed for the purpose of diagnosing various disorders affecting thoracic bones, the chest walls, and structures encompassed inside the thoracic cavity, such as the heart, lungs, and major blood veins. Chest radiography is a frequently used diagnostic modality for the identification of pneumonia and congestive heart failure [1]. Nevertheless, chest x-rays have found to be efficacious in the screening of certain chest disorders, despite their limitations in providing a definitive diagnosis. When there is a suspicion of a problem based on chest radiography, it might be necessary to carry out additional chest imaging in order to make a firm diagnosis or gather proof for the one the initial chest radiography suggested. A chest x-ray is not deemed necessary unless there is suspicion of a displaced, cracked rib that may potentially result in harm to the lungs and other tissue structures [1, 2].

A chest x-ray can find problems in the following areas: airways, breast shadows or bones, cardiac silhouette, costophrenic, diaphragm and extra [3, 4]. Although chest radiography is a cost-effective and relatively low-risk approach for examining chest ailments, it is necessary to note that certain significant chest disorders can be present despite the appearance of a normal chest x-ray. As an illustration, it is possible for a patient diagnosed with acute myocardial infarction to exhibit a chest x-ray that appears entirely normal. Hence, it may be imperative to do further evaluation in order to establish a conclusive diagnosis [4].

Cardiomegaly is a health condition that the heart is enlargement, wherein its size exceeds 50% of the inner diameter of the rib cage [5]. Therefore, the timely cardiomegaly identification is a consequence of diagnosing associated symptoms. The cardiac dimension's evaluation using chest radiography continues to be a valuable diagnostic measure and significant. A chest x-ray makes it easy to find the cardiothoracic ratio (CTR), which can accurately identify heart enlargement and predict cardiomegaly with a 95% success rate. So, the early detection of this disease can help the medical system to reduce the number of infections cases or death rate based on Artificial Intelligence techniques [6].

Medical Technology is commonly used to encompass a several of instruments that empower healthcare practitioners to improve the well-being

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of patients and society. These tools achieve this by facilitating early detection of ailments, minimizing complications, optimizing treatment approaches, offering less intrusive alternatives, and shortening hospital stays [7]. Prior to the advent of mobile technology, medical technologies primarily consisted of traditional medical devices such as prosthetics, stents, and implants. AI led to a huge revolution in the medical technologies field. It is subfield of computer science that specializes in addressing intricate issues, particularly in domains characterized by vast datasets and limited theoretical frameworks [7, 8]. For example, smartphones have become a popular tool for distributing and filling monitoring vital functions through biosensors, electronic personal health information, and promoting optimal therapeutic compliance. As a result, patients are empowered to take on a central role in their own care pathway [7]. The timely identification of cardiomegaly serves as a significant indicator for several cardiac conditions like cardiomyopathy, coronary artery disease, hypertension, infectious ailments, and renal disease. The radiographic assessment of cardiomegaly involves the utilization of the cardiothoracic ratio (CTR), which is a commonly employed metric that offers valuable prognostic insights [9]. Regrettably, the assessment of the cardiac-to-thoracic ratio (CTR) in chest x-ray (CXR) pictures is currently performed manually, resulting in a significant time requirement. Additionally, there exist illnesses that are linked to an increased cardio mediastinal silhouette, which might impede the process of making therapeutic decisions. The utilization of deep learning techniques, namely convolutional neural networks (ConvNets), can improve the effectiveness of analyzing extensive and intricate medical examinations.

ConvNets employ raw picture pixel data as input and progressively extract abstract representations of the original image data, thereby facilitating the possibility of automating the assessment of coronary artery calcium scoring [9, 10]. The provision of a tool to aid radiologists in their interpretations would afford them the opportunity to allocate more time to patient interactions. Additionally, the availability of a tool allowing patients to seek a second opinion could potentially mitigate instances of misinterpretation and enhance the overall quality of healthcare delivery [11].

The remainder sections for this paper are as follow: Section 2 describes the previous papers that related to cardiomegaly detection using different algorithms. Section 3 presents the proposed methodology used in terms of datasets, data preprocessing, feature extraction, and deep learning models. Section 4 illustrates the experimental results and discusses them. Finally, in section 5, the conclusion of the paper and suggest some future work.

2. LITERATURE REVIEW

Table 2 summarizes the previous papers that applied different deep learning algorithms to the cardiomegaly dataset to classify and detect the cardiomegaly disease.

Chamveha et al. [12] put forth a computational method for determining the cardiothoracic ratio (CTR) based on radiographic images of the chest. They employed a U-Net architecture with a VGG16. This model was employed to extract heart and lung masks based on images of the chest X-ray. The dataset used contains 245 images labelled with heart and lung masks from JSRT dataset. Images of the chest X-ray within the dataset were collected using various equipment from diverse hospitals. Consequently, there exists variation in the image intensity, necessitating the normalization of these images prior to their utilizations in a deep learning model. They employed the technique of histogram equalization in order to standardize the photographs. Subsequently, the extent of these masks was used to determine the CTR. The CTR measurements were assessed by human radiologists, and it was determined that 76.5% of them were deemed suitable for inclusion in medical reports without requiring any modifications. The outcome of this study indicated a significant reduction in time and labour for radiologists who utilize their automated solutions.

To efficiently diagnose and localize cardiomegaly, Innat et al [13] introduced a deep learning model, which is called Cardio-XAttentionNet. To create a lightweight and efficient Attention Mapping Mechanism, they reexamined

the global average pooling system and incorporate a weighting term. The model allowed pixel-level localization only from two levels: image labeling and image classification for the cardiomegaly categorization based on chest X-rays. To create Cardio-XAttentionNet, they used some of the most sophisticated ConvNet architectures as the foundational basis for the suggested attention mapping network. ChestX-Ray14, a freely available chest X-ray dataset, is used to build the suggested model. For the classification of the cardiomegaly, the better model obtained a F1-score of 0.86, precision of 0.87, AUC value of 0.89, and recall of 0.85.

Zhou et al. [14] utilized deep learning techniques (InceptionV3, ResNet-50, and Xception) to detect and classify instances of cardiomegaly based on images of the X-ray. They used the "ChestX-ray8" database as input for the techniques that consists of 108,948 X-ray scans spanning the period from 1992 to 2015. For this study, a total of 21,966 images were chosen. Out of the total number of images, specifically 767 instances were classified as "cardiomegaly," while the remaining images were categorized as "healthy." This dataset is divided into training that contains 20,899 healthy images, 467 cardiomegaly images and testing dataset that contains 300 images. The testing dataset split into two categories: "cardiomegaly" and "healthy". The division of the training and testing sets was conducted in this manner as a result of the constrained quantity of images that were annotated with the label "cardiomegaly". The InceptionV3 & ResNet-50 gave the best accuracy of 0.797 in prediction process.

Bougias et al. [15] used four distinct transfer learning algorithms to detect the occurrence of cardiomegaly relied on chest X-rays. They compared and assessed the algorithms diagnostic capabilities by employing the radiologists' reports as the benchmark for accuracy. They employed 2000 chest X-rays that divided into 1000 were classified as normal, and 1000 cardiomegaly individuals. The number of deep features were retrieved from various networks, including SqueezeNet, VGG16, Google's Inception V3, and VGG19 are 2048 features. In this study, a logistic regression technique was employed, which was improved in terms of regularization, to classify chest X-rays into two categories: those indicating the absence or presence of cardiomegaly. They used a logistic regression technique to classify chest X-rays into cardiomegaly or not. The authors used five metrics to evaluate the techniques performance: accuracy, Positive Predictive Value (PPV), sensitivity, Negative Predictive Value (NPV), and specificity. The VGG19 network gave the best performance in terms of accuracy value that is 84.5%.

Chen et al. [16] developed a deep learning models to estimate CXR images in the context of quick cardiomegaly screening based on two labels: cardiomegaly or not, which the model is called high-dimensional multiple regression analysis (MRA). They conducted the tests relied on the chest x-rays dataset gathered from the Clinical Centre in USA: National Institutes of Health CXR Image Database. Model evaluation was conducted using a 10-fold cross-validation approach, and used four evaluation metrics: recall, accuracy, F1-score, and precision. They have shown that the MRA Estimator gave the higher results based on accuracy with 86.28%.

TABLE I. PREVIOUS PAPERS SUMMARIZATION

REF	YEAR	ALGORITHMS	DATASET	EVALUATION METRICS	RESULTS
[12]	2020	U-NET ARCHITECTURE WITH A VGG16	245 IMAGES	ACCURACY	ACCURACY 76.5%
[13]	2023	CARDIO-XATTENTIONNET	CHEST X-RAY14	F1-SCIRE PRECISION AUC RECALL	AUC = 0.89
[14]	2019	INCEPTIONV3 RESNET-50 XCEPTION	21,966 IMAGES FROM CHEST X-RAY8	ACCURACY F1 SCORE	ACCURACY OF INCEPTIONV3 & RESNET-50 = 0.797
[15]	2021	GOOGLE'S INCEPTION V3 VGG16 VGG19 SQUEEZENET	2000 CHEST X-RAYS	ACCURACY SENSITIVITY SPECIFICITY PPV NPV	VGG19 ACCURACY = 84.5%
[16]	2023	MULTIPLE REGRESSION ANALYSIS	112,000 IMAGES FROM CHEST X-RAY8 DATASET	PRECISION RECALL ACCURACY F1 SCORE	ACCURACY = 86.28%
[17]	2023	CXRDANET	CHEST X-RAY14 NLM-CXR	ACCURACY SENSITIVITY SPECIFICITY F1 SCORE AUC	ACCURACY = 0.9050
[18]	2020	TRANSFER LEARNING	952 CHEST X-RAY IMAGES	ACCURACY	ACCURACY = 82%

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[19]	2021	DENSE CONVOLUTIONAL NEURAL NETWORK	CHEST X-RAY DATASETS	AUROC	AUROC = 82.9

3. METHOLOGY

Fig. 1. shows the proposed methodology used in this paper to detect and classify the chest x-ray into cardiomegaly or health. This proposed methodology contains the dataset, the preprocessing steps applied, the data augmentation techniques, and the deep learning algorithms used.

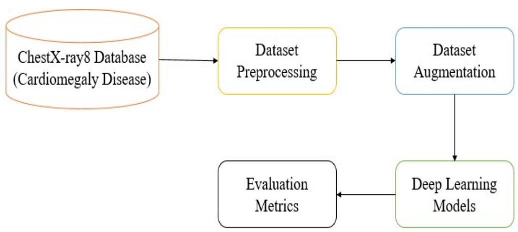

Fig. 1. *Flow Chart Of Proposed Methodology*

DATASET OVERVIEW

In this study, we provide a novel database called "ChestX-ray8" that contains 108,948 X-ray images obtained from 32,717 distinct individuals. This dataset contains 8 diseases: are pneumothorax, cardiomegaly, atelectasis, mass, nodule, pneumonia, infiltration, and effusion. We used the chest x-ray for the Cardiomegaly disease, and the other diseases are labelled as healthy in order to classify the images as Cardiomegaly or not. From these images, the number of images related to the Cardiomegaly is 4,000 chest x-rays images.

Fig. 2. shows the sample of dataset in CSV format that describe each image with their features like image index, label (disease type), patient ID, width, height, age, and position.

	Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImage[Width	Height]	OriginalImagePixelSpacing[x	y]
28265	00007355_007.png	No Finding	7	7355	52	F	PA	2992	2991	0.143	0.143
29623	00007713_003.png	Emphysema|Infiltration	3	7713	54	F	PA	2048	2500	0.168	0.168
62552	00015494_000.png	No Finding	0	15494	80	F	PA	2982	2991	0.143	0.143
79203	00019441_000.png	Effusion|Mass|Nodule	0	19441	38	M	PA	2990	2991	0.143	0.143
35093	00009257_001.png	Cardiomegaly|Infiltration	1	9257	29	M	AP	2500	2048	0.168	0.168
47139	00012010_042.png	No Finding	42	12010	54	M	AP	2500	2048	0.168	0.168
83142	00020427_004.png	Effusion|Emphysema|Pneumothorax	4	20427	18	M	AP	2844	2544	0.139	0.139
11607	00003029_023.png	No Finding	23	3029	54	F	AP	3056	2544	0.139	0.139
46812	00011946_002.png	No Finding	2	11946	38	M	AP	2500	2048	0.168	0.168
10318	00002673_014.png	Consolidation|Effusion	14	2673	25	M	AP	2048	2500	0.168	0.168

Fig. 2. *Dataset Samples*

DATASET PREPROCESSING

Prior to further analysis, the images need to undergo a preprocessing stage. This encompasses several modifications, such as alterations to the dimensions, alignment, and hue. The objective of pre-processing is to enhance the quality of an image, hence facilitating more effective analysis. Preprocessing techniques enable the removal of undesirable distortions and enhancement of key attributes that are crucial for the particular application under consideration. The aforementioned features have the potential to vary according on the specific application. Image preprocessing is an important step to make the dataset suitable for the next process. In this dataset, we resizing the images into fixed size with 512 x 512.

The dataset is split into validation, training, and testing groups. The training dataset indicates to the dataset used in building the model, while the testing set indicates to the dataset used in evaluating the VGG16 model after the model is built. Finally, the validation dataset indicates to the dataset used in evaluating the model during the training process in order to increase the accuracy and handle the overfitting issue. The size of training dataset is 70% and the testing dataset is 30% that divided into two sets: 40% of testing dataset is validation and the remainder is testing.

DATASET AUGMENTATION

DA is a method that used to increase the training set by establishing modified replicas of a dataset based on existing data. The following list comprises several frequently encountered examples:

- The functionality of the system allows for the rotation of images at various angles, such as 90 and 180 degrees. This feature is beneficial in cases where a model is required to accurately detect and classify items that are positioned at various angles. One often employed augmentation technique involves the application of a rotation of 90 degrees.
- The random crop operation involves the cropping of an image at a randomly selected place. This phenomenon may lead to the occurrence of cropping, wherein an object is partially obscured, hence facilitating the model's enhanced ability to recognize objects that are not completely visible.
- The process of exposure involves adjusting the brightness levels of an image, either by

increasing or decreasing them. This feature proves advantageous when a model is anticipated to be employed in environments characterized by varying lighting conditions.

- The blur effect can be applied to an image.
- The function "Flip" allows for the vertical or horizontal mirroring of an image. It is advisable to refrain from employing this augmentation in the event that one is engaged in the task of text recognition.
- Saturation refers to the alteration of color intensity within an image. This enhancement proves to be advantageous in scenarios where the lighting conditions inside the manufacturing area exhibit variability.
- The technique of introducing random noise involves the application of white and black pixels throughout an image. This phenomenon results in a decrease in visual clarity.
- The technique of mosaic augmentation involves the integration of many images into a cohesive whole. Aerial imaging projects can greatly benefit from the utilization of this particular tool.

In our experiments, we used the Random Brightness with [0.7, 1.5], Random Rotations with 3, and Random Zoom = 0.125. Fig. 3. presents the part of Python code that are related to the resize the image to same size and the augmentation technique based on ImageDataGenerator.

```
IMG_SIZE = (512, 512)
core_idg = ImageDataGenerator(samplewise_center=False,
                              samplewise_std_normalization=False,
                              horizontal_flip=False,
                              vertical_flip=False,
                              height_shift_range=0.1,
                              width_shift_range=0.1,
                              brightness_range=[0.7, 1.5],
                              rotation_range=3,
                              shear_range=0.01,
                              fill_mode='nearest',
                              zoom_range=0.125,
                             preprocessing_function=preprocess_input)
```

Fig. 3. Data Augmentation Techniques With Parameters

Before deep learning model is developed, we generated the training, and validation, and testing based on data augmentation technique based on target label, target size is based om given image size, color mode is rgb, and the batch size (8 in training, 400 in testing and 256 in validation). The target label must be determined because the dataset contains 8 diseases, which the target size is Cardiomegaly.

Fig. 4. shows the sample of the chest X-rays from the dataset after the data preprocessing and data augmentation were applied.

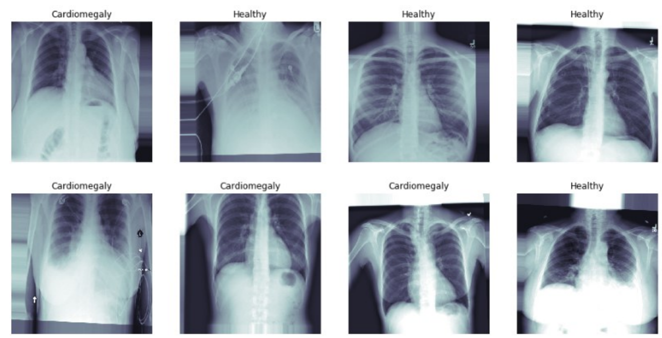

Fig. 4. Sample Of Chest X-Rays

DEEP LEARNING MODEL

We used the CNN (Convolutional neural networks) version to accomplish the detection and classification task, which is called VGG16. CNNs are utilized for clustering images based on their similarities, facilitating efficient images search capabilities. Moreover, these networks are capable of recognizing objects inside complex situations. CNN is commonly employed in the identification of various visual elements, such as faces, persons, street signs, tumours, and platypuses (or platypi) [19].

The triumph of a deep convolutional architecture known as AlexNet in the 2012 ImageNet competition reverberated globally. CNN is playing a pivotal role in generating significant progress in the field of computer vision. This technological advancement holds great potential for various domains such as autonomous vehicles, robots, unmanned aerial vehicles, security systems, medical diagnostics, and interventions for individuals with visual impairments [20].

Convolutional networks provide the capability to undertake mundane business-related tasks, which are both financially advantageous and less complex. For instance, they can be employed for optical character recognition (OCR) purposes, facilitating the conversion of text into digital format. This enables the application of natural language processing techniques to analogue and handwritten documents, where the images represent symbols that need to be transcribed. CNN exhibit versatility outside the domain of image recognition. Text analytics has witnessed the direct use of these techniques [20].

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These techniques can be employed to analyze sound when it is visually displayed as a spectrogram and to process data using graph convolutional networks [20]. The term "VGG16" is used to denote the VGG model, which is alternatively known as VGGNet. The model in question is a CNN with 16 layers. The VGG16 model has demonstrated an accuracy of 92.7% based on the ImageNet dataset. This dataset contains more than 14 million training images spanning 1000 distinct object classes. This particular model holds a prominent position among the models that participated in the ILSVRC-2014 competition. Fig. 5. presents the part of code for the VGG16 model that contains base-pretrained-model that refers to VGG16, and attention model.
Fig. 6. shows the VGG16 model summary after the model is run.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 16, 16, 512)       14714688
_________________________________________________________________
attention_model (Model)      (None, 1)                 138690
=================================================================
Total params: 14,853,378
Trainable params: 137,154
Non-trainable params: 14,716,224
_________________________________________________________________
```

Fig. 6. VGG16 Architecture.

Figure 7 shows the part of code that are related to the components of the attention model. These components are: three conventional 2D layers with different parameters, Average Pool 2D layer followed by the last conventional 2D layer.

```
attn_layer = Conv2D(128, kernel_size = (1,1), padding = 'same', activation = 'elu')
(bn_features)
attn_layer = Conv2D(32, kernel_size = (1,1), padding = 'same', activation = 'elu')
(attn_layer)
attn_layer = Conv2D(16, kernel_size = (1,1), padding = 'same', activation = 'elu')
(attn_layer)
attn_layer = AvgPool2D((2,2), strides = (1,1), padding = 'same')(attn_layer)
attn_layer = Conv2D(1, kernel_size = (1,1),
                    padding = 'valid',
                    activation = 'sigmoid',
                   name='AttentionMap2D')(attn_layer)
```

Figure 7: Attention Model

4. EXPERIMENTAL RESULTS

We explained the findings that obtained after applied the VGG16 model based on following evaluation metrics: recall, accuracy, f1-score, and precision. The following formulas are used to calculate these metrics: FN = False Negative, TN = True Negative, TP = True Positive, and FP = False Positive:

1. Accuracy: The most understandable performance statistic is the ratio of correctly predicted samples to all samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2. Precision: is measured by the percentage of accurately estimated positive samples to all actual positive samples whether true or positive.

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

3. Recall: is the percentage of correctly estimated positive samples to all true positive and false negative instances.

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

4. F1-score: it is the calculated based on the average of precision and recall.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

We conducted many experiments on this dataset with different parameters of the VGG16 like batch size, number of epochs, and test ratio in prediction process.
In the first experiment, we put the value for the aforementioned parameters as followings: batch size = 4, number of epochs = 50, verbose = true, and used the validation data. Table 2 shows the results of the first experiment.

TABLE II. *First Experiments Results*

Model	Accuracy	Precision	Recall	F1-score
VGG16	76	77	76	77

In the second experiment, we put the value for the aforementioned parameters as followings: batch size = 32, number of epochs = 50, verbose = true, and used the validation data. Table 3 shows the results of the second experiment.

TABLE III. *First Experiments Results*

Model	Accuracy	Precision	Recall	F1-score
VGG16	81	83	81	81

In the third experiment, we put the value for the aforementioned parameters as followings: batch size = 128, number of epochs = 50, verbose = true, and used the validation data. Table 4 shows the results of the third experiment.

TABLE IV. *Third Experiments Results*

Model	Accuracy	Precision	Recall	F1-score
VGG16	89	88	89	88

In the fourth experiment, we put the value for the aforementioned parameters as followings: batch size = 128, number of epochs = 50 and verbose = true. Table 5 shows the results of the fourth experiment.

TABLE V. *Fourth Experiments Results*

Model	Accuracy	Precision	Recall	F1-score
VGG16	91	90	92	91

Figure 8 shows the performance results for all experiments that were conducted based on the VGG-16 model. The results showed that the values of the parameters in the final experiments were high compared with the other experiments.

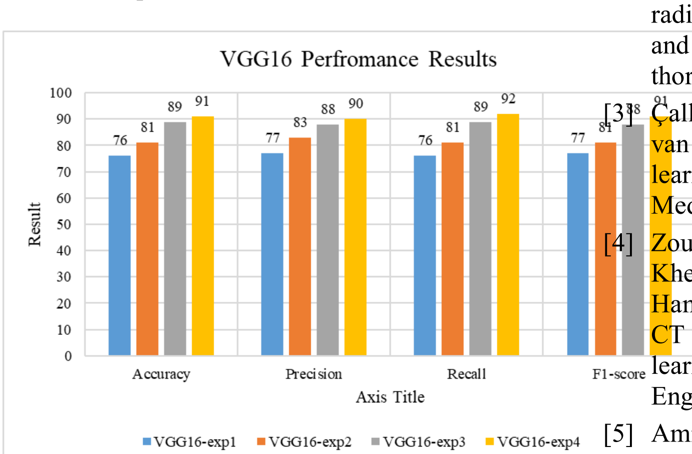

Fig. 8. Performance Results – All Experiments

5. CONCLUSION AND FUTURE WORK

We deveploed a deep learning method to classify and identify chest X-rays, regardless of whether they are cardiomegaly or connected to health. First, we used the ChestX-ray8 dataset that is a collection of medical images related to a variety of illnesses, including cardiomegaly. Subsequently, we performed the preprocessing operations on the dataset, such as resizing and normalizing each image. It should use data augmentation techniques like random zoom, random rotation, and random brightness before using the deep learning techniques. The VGG16 is the deep learning technique that is being employed. When compared to previous works, the VGG16 model obtains a high accuracy of 91%, according to the data.

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