PNEUMONIA DETECTION

USING IMAGE PROCESSING TECHNIQUES

This file contains Project on Pneumonia Detection which is made by **MTech Integrated** Software Engineering Students of **VIT VELLORE** under the Guidance of **Prof.Prabhukumar** in their Jth Component Course (Digital Imaging Processing).

Domain- Medical Imaging

Pneumonia Detection in Lungs

Digital Image Processing

SWE1010, F1+TF1

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Table of Contents

ABSTRACT:

Pneumonia is an infection that inflames the air sacs in one or both lungs.

With pneumonia, the air sacs may fill with fluid or pus. The infection can be life-threatening to anyone and with this Covid 19 situation, Covid pneumonia is also increasing at a higher rate.

In the case of COVID pneumonia, the damage to the lungs is caused by the coronavirus.

In this project we will be detecting pneumonia in affected lung by using image processing techniques (Image Enhancement, Segmentation etc.) performed in python programming language along with a CNN (convolutional neural network) models.

LITERATURE REVIEW:

Vandecia Fernandes et al. [1] proposes Bayesian optimization to detect pneumonia and determine whether it is viral or bacterial. It also uses specific convolutional neural network architecture for detection and pre-trained networks. This journal provides an accuracy of 0.964 for pneumonia detection and 0.957 for type of pneumonia. This proves that the proposed model is way efficient than traditional methods like histogram equalization and lung segmentation. The results were comparatively better than other network and architecture.

Adhiyaman Manickam et al. [2] preprocesses input X-Ray and identify pneumonia using U-net architecture. It identifies normal and abnormal pneumonia using pre trained ImageNet dataset. The models used are

ResNet50, InceptionV3, InceptionResNetV2. Adam and Stochastic Gradient Descent (SGD) were used as optimizers to extract features and improve accuracy of trained models. The accuracy for ResNet was 93.06%, precision rate = 96.78% and recall rate = 92.71%.

Rachna Jain et al. [3] trains several CNNs model to classify X-ray images whether they have pneumonia or not using various parameters and hyperparameters. The pretrain models used were VGG16, VGG19, ResNet50 and Inception-v3, their accuracies were 87.28%, 88.46%, 77.56% and 70.99% respectively. First and second model have two and three convolutional network layers respectively.

Xiang Yu et al. [4] has three components like feature extraction, graph-based reconstruction and classification. It uses transfer learning to train CNNs for binary classification. A shallow neural network uses GNet combined network as input and classify the type of pneumonia. The model had an accuracy of 0.9872 at sensitivity 1 and specificity at 0.9795. Images were not squared and properly cropped which were done using deep network.

Victor Ikechukwu A et al. [5] proposes a comparison between pre trained model VGG-19 and ResNet-50 against training from scratch a model like Iyke-Net. The dataset was divided into training, testing and validation set Training and validation results suggests that VGG-19 and ResNet-50 were better with a recall 92.03%.

Marco La Salvia et al. [6] has used deep learning and lung ultra sound technologies along with CNN for detecting Covid-19 Pneumonia. They have used ResNet18 and ResNet50, augmentation and transfer learning for conducting their study.

Devvret Verma et al. [9] have prepared a framework that classify between ptb,viral and bacterial pneumonia from the dataset. They have used neural network classifier.in the end of this paper, they were able to produce accuracy of 99.01%.

Anand Nayyar et al. [10] proposed a novel approach to make an automated diagnosis and identify the affected region in lungs. They have used MASK RCNN object detector.in the end, they got a IoU score of 0.155 which is better than previous studies or methods.

Amit Kumar Jaiswal et al. [11] proposes an identification model based on Mask-RCNN which aids in pixel-wise segmentation. Threshold in the background along with image augmentation improved the quality of output. This model was deveploped on ResNet50 and ResNet101. Intersection over union, mean threshold value and mean score was useful in measuring the performance. Data augmentation helped in increasing or decreasing the brightness, adjusting the contrast and correcting blur.

Yadavendra et al. [15] here Mask-RCNN is used on input X-ray images of chest for detection and segmentation of region of lungs where pneumonia is found. Mask-RCNN has been trained for the dataset which also find loss with the help of loss function. Due to this pneumonia lung opacity was easily detected

Devansh Srivastav et al. [12] have used deep learning algorithms for the classification of chest x ray images to detect pneumonia. Transfer learning was used along with CNN by utilising VGG16 for image classifciation.in the end they were able to achieve 94.5 accuracy which was higher than previous models.

Heewon Ko et al. [13] have detected pneumonia using an ensemble of deep cnn. moreover, r-cnn ,retinanet,rsna, kaggle are also used. For classifier, resnet is used which increased the accuracy and increased the value of map up to 0.21592.

Sobain Jamil et al. [14] have used a novel algorithm based on Alex Net and have compared their result with existing CNN methods.

Dina M.Ibrahim et al.[17] have used GitHub and rsna as a dataset. For image enhancement they have used data normalization, for data restoration- augmentation and for segmentation they have used CNN along with rnn. for detecting pneumonia. their method was able to archive an accuracy of 98.05%.

Md. Jahin Alam et al. [18] mentioned their study as a structure to automate the pneumonia detection process by introducing a robust deep learning framework. In this paper Process Convolution (Pro Conv) blocks for feature accumulation inside Dual Feedback (DF) blocks to propagate the feature maps towards a viable detection was used

WeiqiuJin et al.[19] have proposed a three-step hybrid ensemble model, including a feature extractor, a feature selector, and a classifier.(AlexNet, ReliefF algorithm, trial-and-error approach).at last they concluded that proposed model in this article is practical and effective, and can provide high-precision COVID-19 CXR detection.

FranciscoDorr et.al [20] have detected pneumonia with artificial intelligence. Under ai they have used AUROC technologies which was able to increase the diagnostic sensitivity from 47% to 61%.

Ali Narin. [22] have used Deep learning models and traditional machine learning methods were used together. The performances of the features selected by the meta-heuristic PSO and ACO feature selection methods were examined. High detection accuracy (99.86%) was obtained using deep features with PSO and SVM.

Abhishek Sharma. [28] has identified the lung region by rib cage boundary identification and would be computing the area of this region.He has also used Otsu thresholding to segregate the pneumonia cloud from the healthy lung in the lung area, still we are working on other methods that can be adopted for thresholding the CXR images which can yield better results.

Mohammad Momeny. [29] has introduced noising- and denoising-based data augmenters to improve the generalization of a deep CNN. The proposed method performs better results compared to the state-of-the-art learning to augment strategies in terms of sensitivity (0.808), specificity (0.915), and F-Measure (0.737).

P. K. Pawłowski. [32] have implemented Convolutional Neural Network (CNN), which is the deep learning method and tries extract each and every feature init. The dataset used was from Kaggle, online open-source platform to machine learning.

Mohammad E H.[35] have used Deep convolutional neural networks typically perform better with a larger dataset than a smaller one. Transfer learning can be used in the training of deep CNNs where the dataset is not large.

Hao Ren. [37] has proposed a multi-data and interpretive medical-assisted diagnosis model for pneumonia, and we have created a largescale dataset of pneumonia diagnosis annotated by respiratory specialists. He has classified pneumonia deeper, such as to determine whether it is bacteria, viruses, or fungi.

Chongyan Chen. [40] has proposed a framework that leverages radiomic features and contrastive learning to detect pneumonia in chest X-ray. Also has mentioned the use of Contrastive Training which is framework that learns similar/dissimilar representations from data that are organized into similar/dissimilar pairs.

Ayush Pant. [42] has included Jointly Learning Convolutional Representations to Compress Radiological Images and Classify Thoracic Diseases in the Compressed Domain. To tackle the problem of having noise in the image Gaussian blur which is also known as

Gaussian smoothing is used, which will help in reducing noise in the image.

Min-Jen Tsai. [46] here examines the important statistical features including use the Convolutional Layer, ReLU Layer and Pooling Layer for Chest X-rays identification by using Convolutional Neural Network (CNN) and decision fusion of feature selection.

Using machine learning it is found that the operation of the neuron system is hierarchical based on the functional analysis of the cortex cells of the cat to find the corresponding relationship between neurons.

Chinthiya Hayat. [49] has used Data Collection, CNN Procedure, Convolutional Neural Network (CNN), Area Under the Receiver Operating Characteristic Curve (AUROC). AUROC analysis on the training results of the best re-sampling dataset is obtained at modification 16 at 5% dataset - 80–20 holdout.

LITERATURE SURVEY:

S.No	Paper	Image acquization or datasets	Image Enhancement	Image Restoration	Image segmentation	Features Extraction	Classifiers	Quality Metrics & Results	Remark
1	Bayesian convolutional neural network estimation for pediatric pneumonia detection and diagnosis	ChestX-ray14	-	Data augmentation	OCT layer segmentation	DenseNet121	L1-SVM	Detection=0.964 Accuracy for pneumonia type classification=0.957	Architecture proposed is specialized to the problem, which guarantees greater adaptability to the variance of exams
2	Automated pneumonia detection on chest X-ray images: A deep learning approach with different optimizers and transfer learning architectures	ImageNet	Histogram equalization.	--	U-Net architecture	ConvNet	3D fully CNN	The experimental results achieved the accuracy 93.06%, 92.97%, and 92.40% for ResNet50, InceptionV3 and InceptionResNetV2 proposed model	Deep learning methods offered much better results than traditional methods in terms of quality of treatment and accuracy
3	Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning	Kaggle	-	-	The convolutional layer, the pooling layer, flattening layer, and the fully-connected layer	CNN Models	ResNet	Model 2 and VGG19 networks obtained high f1 scores of 94% and 91% respectively	Improve the classification accuracy of all the models by fine-tuning every parameter and hyper-parameter
4	CGNet: A graph-knowledge embedded convolutional neural network for detection of pneumonia	Chest X-Ray Images (Pneumonia) 2020	Gamma correction	-	K neighbours	Transfer learning	GNet	Accuracy=0.99 Specificity=1 Sensitivity=0.98	The performance of reconstruction could be significantly affected by the distribution of features in the same batch. The validation set in the dataset involved is too small to act as a useful validation set.
5	ResNet-50 vs VGG-19 vs Training from Scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest x-ray images	ImageNet with modified optimizers	Calibration, registration, and transformation	Data augmentation	Clustering, edge detection, threshold and vector quantization	CNN algorithms	Softmax	RESNET-50 Accuracy=96.2 Precision=95.3 Recall=98.4 VGG-19 Accuracy=97.3 Precision=96.7 Recall=99.2	With a recall of 92.03%, our analysis showed that the pre-trained models liker RESNET AND VGG with proper finetuning was comparable with lyke-Net, a CNN trained from scratch.
6	Deep learning and lung ultrasound for Covid-19 pneumonia detection and severity classification	ImageNet	Batch normalisation	Abdominal settings, focusing on the pleural line, reaching a depth of 10 cm with the convex probe	Pixel-based ML motion	Deep residual networks	ResNet18 ResNet50	F1-score results ranging from 66% to 99% for the different architectures considered. Nonetheless, metrics are above 97% in all cases.	This study provides an approach for overcoming the dataset problems concerning the scoring inconsistencies between ultrasounds due to different physicians scoring different lungs of the same stage
7	A Deep Feature Learning Model for Pneumonia Detection Applying a Combination of mRMR Feature Selection and Machine Learning Models	The dataset was collected by taking the chest X-ray images of the volunteer patients.	mRMR and spatial domain methods	--	CNN(through backpropagation algorithm)	AlexNet, VGG-16, and VGG-19 CNN models	k-nearest neighbors and LDA	Accuracy=99.41 Sensi=99.61 Specificity=99.22	Deep features provided robust and consistent features for pneumonia detection, and the mRMR method increased the efficiency of the classification.
8	Viral Pneumonia Screening on Chest X-Rays Using Confidence-Aware Anomaly Detection	X-VIRAL	CLAHE	_	Deep segmentation-emendation model	Confidence-aware anomaly detection (CAAD)	ConfidNet	AUC of 83.61% Sensitivity of 71.70%	Nomaly detection works well in term of viral pneumonia screening on chest X-ray images and is superior to binary classification methods
9	An efficient framework for identification of Tuberculosis and Pneumonia in chest X-ray images using Neural Network	Shenzhen chest X-ray and China dataset	--	Data augmentation methods	Neural Networks	Feature map	Neural network classifier	Accuracy=99.01%	The previous works in this field have accuracy less than ours because they took the height and width of the image into consideration but the depth information was lost. And in our framework, we have taken images at different angles and shifting the images horizontally and vertically and rescaling the it

10	Quantitative Analysis and Automated Lung Ultrasound Scoring for Evaluating COVID-19 Pneumonia With Neural Networks	Huoshenshan Hospital	Computer-aided analysis	Curve-to-linear conversion	-	Region-of-interest (ROI) selection	Support vector machines and decision trees	The model with 128×256 two fully connected layers gave the best accuracy of 87%	The proposed automated LUSS model has the potential to be integrated into portable and mobile ultrasound equipment for clinical use in hospitals of different levels as well as prehospital settings such as the ambulance
11	Identifying pneumonia in chest X-rays: A deep learning approach	The dataset was collected by taking the chest X-ray images of the volunteer patients.	Image Augmentation	Image Augmentation	Mask-RCNN, a deep neural network which incorporates global and local features for pixel-wise segmentation	Convolutional features	ROIAlign	Developed different CNN architectures and obtained promising results with 85 percent sensitivity.	Model can be improved by adding new layers, but this would introduce even more hyperparameters that should be adjusted.
12	Customized VGG19 Architecture for Pneumonia Detection in Chest X-Rays	Conventional chest radiographs	Threshold filter	-	Deep-Learning Scheme	CWT, DWT and GLCM	SVM-linear, SVM-RBF, KNN, Random-Forest (RF) and Decision-Tree (DT)	The result confirms that VGG19 with RF classifier offers better accuracy (95.70%).	Modifying the Fully-connected layer and the drop out layer to enhance the classification accuracy
13	Efficient ensemble for image-based identification of Pneumonia utilizing deep CNN and SGD with warm restarts	ImageNet	Image augmentation	Image augmentation	CNN	-	SVM	Accuracy of 96.26% and AUC of 95.15%	The method exploits the averaging ensemble method and SGDR capabilities to converge and escape from the local minima with warm restarts of the learning rate.
14	A Deep Convolutional Neural Network Based Framework for Pneumonia Detection	Kaggle	Data augmentation	Data augmentation	Automated lesion segmentation	AlexNet	SVM	Accuracy=99.4% F1 score is 0.99. The specificity and sensitivity of AlexNet with SVM are 100% and 98.3% respectively	Computational complexity is also decreased by using AlexNet for feature extraction
15	Pneumonia lung opacity detection and segmentation in chest x-rays by using transfer learning of the Mask R-CNN	Radiological society of North America (RSNA)	-	-	R -CNN	SegNet	Binary mask	The performance of the trained model on a test dataset and find a segmented and detected region of the image of the chest x -rays that portion of the lungs, that is affected from the pneumonia lungs opacity with confidence scores	It can be extended to the detection and segmentation of other chest diseases from chest x -rays
16	Pneumonia Detection through Adaptive Deep Learning Models of Convolutional Neural Networks	Radiological Society of North America (RSNA)	Computer-aided detection (CAD)	Additional stacked layers	CNN	Computer vision and deep convolutional neural networks	AlexNet, GoogleNet, LeNet, StridedNet, ResNet-50, and VGGNet-16.	GoogLeNet and LeNet has accuracy of 98% while the ResNet-50 gained the last among the six models trained with an accuracy rate of 80%. VGG-16, AlexNet, and StridedNet has a mark of 96% to 97%	An adaptation of other convolutional neural network architectures like Inception-v3, shuffle Net, and Mobile Net architectures for pneumonia detection must be implemented
17	Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases	GitHub and RSNA	Data normalization	------	Combination of CNN and recurrent neural network (RNN)	VGG19+CNN	SoftMax activation function	98.05% accuracy, 98.05% recall, 98.43% precision, 99.5% specificity, 99.3% negative predictive value, 98.24% F1 score, 97.7% MCC, and 99.66% AUC, based on X-ray and CT images.	Through extensive experiments and results performed on collected datasets from several sources that contained chest x-ray and CT images, the VGG19+CNN model outperformed the other three proposed models.
18	A Robust CNN Framework with Dual Feedback Feature Accumulation for Detecting Pneumonia Opacity from Chest X-ray Images	Kaggle	CLAHE	Deep network (Inf-Net)	Robust deep convolutional neural network	DF blocks	ResNet50 DenseNet121 VGG19	Accuracy, sensitivity and specificity of 97.78%, 98.84% and 95.04% respectively	Improve the classification accuracy of the model by fine tuning and layer reduction if possible

19	Hybrid ensemble model for differential diagnosis between COVID-19 and common viral pneumonia by chest X-ray radiograph	Covid-chestxray	ReliefF algorithm	ReliefF algorithm	Image fractal features	AlexNet provided by MATLAB	SVM Model	Deep convolutional neural network (DCNN) model, which achieved an accuracy of 93.64% ± 1.42% in distinguishing COVID-19 cases from normal subjects	The components in the hybrid model structure presented in this paper can also be replaced according to the characteristics of the data, which can maintain a good classification effectiveness.
20	Pneumonia Detection Using Deep Learning Approaches	JSRT dataset	Continuous wavelet transformation	Fast Fourier transformation	UNet-based CNN	Rule-based image processing	VGG16	It is observed that VGG16 achieves the highest accuracy so far	It can happen that a disease can be detected even when it is not present due to presence of some other disease and this problem of false disease detection has to be solved
21	COVID-19 pneumonia accurately detected on chest radiographs with artificial intelligence	A total of 302 CXR images from adult patients were randomly sourced from nine different databases	----	---	DenseNet 121 architecture	AUROC, Brier and Mean Absolute Error	Mann-Whitney U statistic	Sensitivity and Specificity for COVID-19 prediction based on CXR by physicians was 47% and 79% respectively, with an increase in sensitivity to 61% (p < 0.001) and a decrease in specificity to 74% (p = 0.007) when using AI support	We showed an increase in sensitivity from 47% to 61% for COVID-19 prediction based on CXR. Future prospective studies are needed to further evaluate the clinical and public health impact of the combined work of physicians and AI systems.
22	Accurate detection of COVID-19 using deep features based on X-Ray images and feature selection methods	K-fold cross validation (CV)	----	----	Computed Tomography (CT)	Convolutional Neural Network (CNN)	Support vector machines (SVM) and k nearest neighbor (k-NN) algorithms	The first reason why CNN models are used in feature extraction is that deep features give very high results in studies in the literature. Secondly, there is a limited number of hybrid approaches using deep attributes to detect COVID-19.	The features selected with PSO and ACO to increase the classification performance also contributed positively to the achievements. It is seen that the features taken from CNN models show very high performances with traditional classification algorithms and feature selection algorithms.
23	X-ray Imagining Based Pneumonia Classification using Deep Learning and Adaptive Clip Limit based CLAHE Algorithm	The pneumonia CXR	CLAHE	Six max-pooling layers	-	Convolutional Neural Network Model	Binary classifier	The CNN model has given the accuracy of 95.52% on Training Data and 94.33% on a Validation set.	Further research may be expanded to develop a model for segmentation of the pneumonia affected area as well as creating a multiclass classification problem for the same.
24	Automated detection of pneumonia in lung ultrasound using deep video classification for COVID-19	LUS dataset AND ImageNet dataset	Batch normalization	Convolution transpose layers	Semi-supervised segmentation	TV-L1 algorithm	-----	Accuracy of 90%, a balanced accuracy of 90%, and an average precision score of 95%	Automated AI analysis of portable US imaging can help triage patients presenting to emergency with flu-like or breathing difficulty symptoms, determine who needs to be hospitalized and immediately identify those patients who require ICU admission.
25	Investigation of the performance of Machine Learning Classifiers for Pneumonia Detection in Chest X-ray Images	Kaggle	Resizing and dimension reduction	CNN	Deep learning techniques	Image Convolution	Decision tree Random Forest	It appears that CNN outperforms all other models by a small margin with a test accuracy score of 98.46%. Random forest performs surprisingly well with a test accuracy score of 97.61%	With proper parameter tuning and giving a little more time, the CNN model could achieves an even better result.
26	Analysis of Various Optimizer on CNN model in the Application of Pneumonia Detection	Kaggle	Adam optimizer	Data Augmentation	RMSProp	CNN	Binary classifier	Adam optimizer had the best result with validation accuracy of 86.94%, validation loss of 34.32%	RMSProp and SGD are the most suitable and reliable optimisers for these sort of problems

27	A Pneumonia Detection Method Based on Improved Convolutional Neural Network	Kaggle	Pneumonia Image Detection System Framework	----	Robust deep convolutional neural network	GoogleNet inception V3 network trained by ImageNet data set to extract features	Support Vector Machine (SVM)	Domestic and foreign scholars have done a lot of research, and the accuracy rate obtained by using transfer learning is 92.80%	On the basis of relevant research, a convolutional neural network based on improved Lenet was proposed to realize the detection of pneumonia images
28	Detection of pneumonia clouds in chest X-ray using image processing approach	Radiological Technology (JSRT) Image	Histogram equalisation	'resize' function of OpenCV.	Thresholding	Indigenous algorithms	----	----	At this stage of the project, we have identified the lung region by rib cage boundary identification and would be computing the area of this region.
29	Learning-to-augment strategy using noisy and denoised data: Improving generalizability of deep CNN for the detection of COVID-19 in X-ray images	Chest X-ray images of posterior–anterior view	Image data augmentation	Data augmentation approach with denoised data	CNN	Reconstruction learning process	When the noisy images are fed as inputs to the network, data augmentation using noise may improve the robustness of the classifier	Data augmentation strategy improved the performance of the CNN from 92.29% to 97.70%.	A noisy data generator, a Bayesian optimizer-based controller, an autoencoder network, child augmenters, and child CNN models are key components of our proposed noising- and denoising-based data augmenter that increase the accuracy of the image classification task.
30	Spectral-based pneumonia detection tool using ultrasound data from pediatric populations	National Institute of Child Health in Lima, Peru	-	Median filter	Custom interface developed on MATLAB	Cellular neural networks	Support vector machines	Results reveal that the specificity, sensitivity and accuracy of the method are above 93%, 80% and 89% respectively	The combination of the portability and relative low price of ultrasound scanners may help to provide pertinent detection on rural or underserved areas of developing countries
31	A Combined Approach Using Image Processing and Deep Learning to Detect Pneumonia from Chest X-Ray Image	OCT and Chest X-Ray	Contrast Limited Adaptive Histogram Equalization	VGG-16	----	------	softmax activation	accuracy of 96.2% using VGG-16 and 95.9% using VGG-19	In order to provide proper treatment to this disease, it needs to be detected in the early stage. Chest X-Ray images provide a way to detect pneumonia fast. But, due to the shortage of radiologists, an automatic detection system that can predict pneumonia precisely is needed.
32	Pneumonia Detection Using Deep Learning Algorithms	Kaggle	----	ReLU	Otsu threshold	Mask-RCNN	Deep learning with DCNNs can precisely characterize TB at chest radiography with an AUC of 0.99.	The accuracy they obtained through this model was 95.4%. The accuracy does consist of conditions. They took the accuracy value when the sensitivity and specificity was maximum, i.e., 0.9 and 0.88.	In each and every problem, like detection, prediction, classification, recommendation systems in medical industry adopting deep learning algorithms for better precise decisions. Moreover, the deep learning algorithms gives the results in no less than time which could be helpful to doctors in case of treatments.
33	Attention Based Residual Network for Effective Detection of COVID-19 and Viral Pneumonia	Kaggle's dataset containing CXR images	CXR imaging	Grad-CAM visualization	IAVP	ResNet architecture	DarkNet model, YOLO	With 97.69% accuracy, the ResNet32 with attention module outperformed other architectures	Transfer learning from the model trained upon larger dataset like ImageNet results in better accuracy than non transfer learning based approach.
34	A Multiple Deep Learner Approach for X-Ray Image-Based Pneumonia Detection	Radiological Society of North America (RSNA)	transfer learning	----	Faster-RCNN	---	ROIAlign classifier	96% of precision	Through automation of the pneumonia diagnosis support system based on MDL, we hope the technology can reduce the burden on healthcare system and healthcare workers.

35	Can AI Help in Screening Viral and COVID-19 Pneumonia?	COVID-19 positive chest X-ray images	Image augmentation, Cystoscopic image analysis	CheXNet which is a 121-layer variant of DenseNet trained on X-ray images	AlexNet and GoogLeNet	Radiographic images including bilateral, multi-focal, ground-glass opacities	Two- and Three-class classifier	The classification accuracy, precision, sensitivity, and specificity for both the schemes were 99.7%, 99.7%, 99.7% and 99.55% and 97.9%, 97.95%, 97.9%, and 98.8%, respectively.	CheXNet which is a variant of DenseNet was outperforming other networks while image augmentation was not used. Moreover, there is a large degree of variability in the input images from the X-ray machines due to the variations of expertise of the radiologist.
36	Improved Classification for Pneumonia Detection using Transfer Learning with GAN based Synthetic Image Augmentation	dataset contains 5856 images of chest X-rays	Augmentation of images	-----	DCGAN architecture	Sigmoidal activation	---	The model achieved an accuracy of 94.5%.	For future work, it is planned to improve the model accuracy and also to classify pneumonia as viral, bacterial or fungal. It is also planned to take the patient's medical history into consideration to predict the probability of pneumonia.
37	Interpretable Pneumonia Detection by Combining Deep Learning and Explainable Models With Multisource Data	Chest X-ray images, Train-CNN	Computed Tomographies (CT), Magnetic Resonance Images (MRI)	----	Grad CAMs	The features are extracted from reports and chest X-ray images are low-dimensional vectors	The value ranges of AUC are from 0.5 to 1. If the AUC is larger, the classifier is better.	MulNet achieves an AUC of 0.87(95% CI 0.82, 0.92), a precision of 0.73(95% CI 0.65, 0.80), a recall of 0.94(95% CI 0.85, 0.98), and an F1-score of 0.82(95% CI 0.74, 0.88).	This model consists of CNN and the Bayesian Network (BN) combined with two types of data: 1) chest X-ray images 2) medical reports. Moreover, the model provides diagnostic explanatory information giving that physicians can have a better understanding of the diagnosis result.
38	Pneumonia Detection Using Image Processing And Deep Learning	Chest X-ray Dataset provided by GLOWM	Histogram equalization	Image Augmentation	---	---	---	Accuracy 96%, Precision 96.20%, Recall score 97.4%	It would be fascinating to see approaches consisting of various other types of image preprocessing
39	An Empirical Study of Dehazing Techniques for Chest X-Ray in Early Detection of Pneumonia	Kaggle	CLAHE	---	---	----	Entropy and NIQE	Average values of clahe and he are-7.48 and 7.37	Dehazing techniques remove the haze from images and improve the quality of images. This experiment is performed on 100 Chest X-Ray images.
40	Pneumonia Detection On Chest X-Ray Using Radiomic Features And Contrastive Learning	RSNA Pneumonia Detection Challenge	Chest X-ray, chest radiology image	ResNet-18Att	Semi-supervised segmentation	The image features extracted by the attention-based convolutional neural network (CNN) model, via a contrastive loss in the latent space.	Pneumonia detection is a binary classification task	We used 75% imaged for training and fine-tuning and 25% for testing.	Experimental results showed that our proposed models could achieve superior performance to baselines. We will compare contrastive learning with multitask learning to further exploit the integration of radiomics with deep learning.
41	Atomatic Detection and Diagnosis of Severe Viral Pneumonia CT Images Based on LDA-SVM	CT image	Fisher LDA and SVM	----	Median filter	Lba and hog	SVM classifier	92.775% accuracy rate	In order to solve the problems of inefficiency, coarse granularity and poor accuracy under the background of large data, LDA-SVM
42	Pneumonia Detection: An Efficient Approach Using Deep Learning	Kaggle	Data Augmentation	Data Augmentation	Automated lesion segmentation	Convolution Neural Network (CNN), this method helps in extracting essential features from the high dimension image.	CT scan, MRI scan	An Accuracy of 0.82 is obtained, with a high Recall value of 0.99 which signifies that there are low false negative values	This model is robust as it can work on any of the datasets that conform to the size of the image that is required for this model. The ensembled model uses the best of both worlds, in that the high Precision quality is drawn from EfficientNet-B4

43	PNet: An Efficient Network for Pneumonia Detection	ChestX-ray14	PNets	---	AlexNet and VGG16	--	Heatmaps	92.79% accuracy and 0.9393 F1	By using small size convolution filters to extract image features, THEY gOt a better result than AlexNet and VGG16 with fewer parameters
44	Comparative Experiment of Convolutional Neural Network (CNN) Models Based on Pneumonia X-ray Images Detection	Kaggle, Chest X-ray	----	Classic Model.VGG16.Residual Network 50	Semantic segmentation	Class Activation Map (CAM	ReLU, Sigmoid, and Tanh	Classic CNN i75%, in VGG16,80%, and in Resnet50,85%	CNN is the most effective means, nowadays, to deal with various pictorial tasks. This work shows the basic idea and functions of different models. We hope other people can gain enlightenment and do the improvement based on this work.
45	Deep Learning based Detection and Segmentation of COVID-19 & Pneumonia on Chest X-ray Image	chestX-ray-dataset	Grad-CAM	---	U-Net	--	DenseNet121	Accuracy-99.2%	In future we have a great fascination to work with more deep learning algorithms to find out the right affected area and work with more X-ray imageS
46	Machine Learning Based Common Radiologist-Level Pneumonia Detection on Chest X-rays	Chest X-rays	SVM	Image augmentation	Deep neural network representations	Convolutional Layer, ReLU Layer and Pooling Layer	Aussian mixture model (GMM) and AdaBoost algorithm.	High classification accuracy rate at 80.90% for 144 layers of neural network which demonstrates promising applications for Chest X-rays identification classification of histological images.	Demonstrates that our identification results achieve the best accuracy rates and our proposed method is superior to the previous studies for Chest X-rays images classification.
47	Exploiting Deep Cross-Slice Features From CT Images For Multi-Class Pneumonia Classification	Chest CT imaging	Convolutional Neural Network(CNN)	----	Lung infection segmentation from CT images	Deep Cross-Slice	Effectiveness of dual-task learning in stage 1	Highest accuracy of 96.23% (95% CI), indicating that our method is incapable of obtaining stronger context information.	There are two-stage framework integrating the multi-scale context feature across slices, which is successfully applied in the task of multi-class pneumonia classification.
48	Pneumonia Detection from Chest X-ray using Transfer Learning	Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images	Computerised Tomography (CT), Chest X-ray	Data augmentation	Edge based segmentation	ResNet, VGG, AlexNet, DenseNet	Transfer learning	DenseNet-121 and has an accuracy of 92.8 % and recall of 93.2 %	Main focus is on CNN models like InceptionV3, ResNet-50, and VGG16 based on Transfer Learning specifically for pneumonia detection.
49	Chest X-Ray Image Analysis to Augment the Decision Making in Diagnosing Pneumonia using Convolutional Neural Networks Algorithm	ChestX-ray14	CXR Image Recognition	PE detection augmentation	Thresholding	CNN, a feed-forward of ANN	AUROC	CXR diagnosis shows that the accuracy could be enhanced by score-based standardization.	AUROC analysis on the training results of the best re-sampling dataset is obtained at modification 16 at 5% dataset - 80–20 holdout.
50	Ensembles of Convolutional Neural Network models for pediatric pneumonia diagnosis	Pediatric X-rays	Image Augmentation	Data Augmentation	Lung segmentation, which removes irrelevant data on X-rays	Clinical images can be analyzed using machine learning methods such as convolutional neural networks (CNN), which learn to extract critical features for the classification	A standard metric derived from the ROC is the Area Under the Curve (AUC)	To analyze the performance of the different models, we used different metrics obtained from the ROC (Receiver Operating Characteristic Curve)	A new Machine Learning system based on ensembles, which combines XAI techniques and CNN models, has been designed for the childhood pneumonia diagnosis.

DATASET:

To accomplish this project, we will be using open-source dataset **KAGGLE** where there are thousands of pictures of chest of both normal and affected lungs.

Links-

https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

Techniques Used

Image Enhancement:

For doing this, we will be using histogram equalization in python along with open cv.

CNN:

A **convolutional neural network** (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data.

Image segmentation:

For this we have used, open cv edge detection method.

Restoration

Image restoration is performed by **reversing the process that blurred the image** and such is performed by imaging a point source and use the point source image, which is called the Point Spread Function (PSF) to restore the image information lost to the blurring process.

Transforming, feature extraction and classifier etc. will also be used.

Transfer learning concepts

Transfer learning is a research problem in machine learning that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem

IMAGE ENHANCEMENT:

Image Enhancement is the procedure of improving the quality and information content of original data before processing. The tools used for image enhancement include many different kinds of software such as filters, image editors and other tools for changing various properties of an entire image or parts of an image.

There are various methods to perform Image Enhancement, they are:

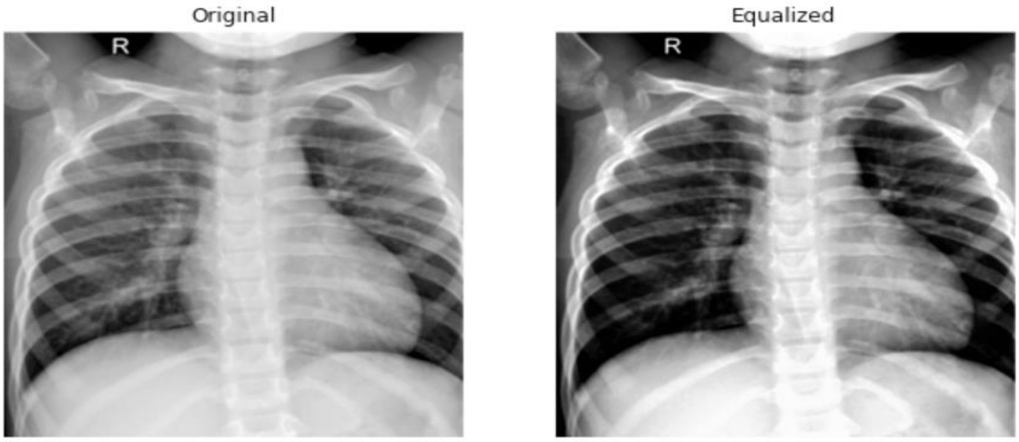
- Histogram Equalization
- Median Filters
- Logarithmic transformation
- Power law transforms
- Unsharp Masking

Among these we have chosen a few of them to perform image enhancement on the images of lungs and will conclude which performs better.

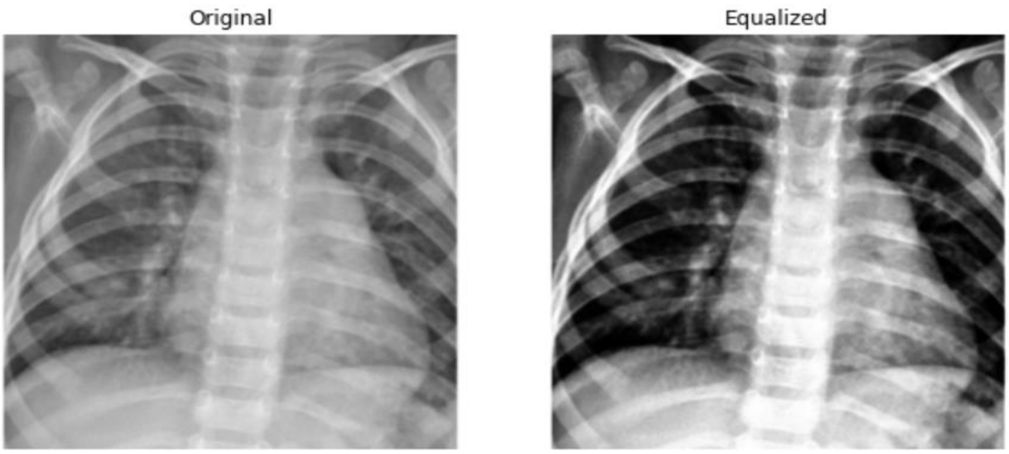
HISTOGRAM EQUALIZATION:

Histogram Equalization is an image processing technique that adjusts the contrast of an image by using its histogram. To enhance the image's contrast, it spreads out the most frequent pixel intensity values or stretches out the intensity range of the image.

Here we have an image of normal lungs on which histogram equalization has been performed.



Here we have an image of pneumonia affected lungs on which histogram equalization has been performed.

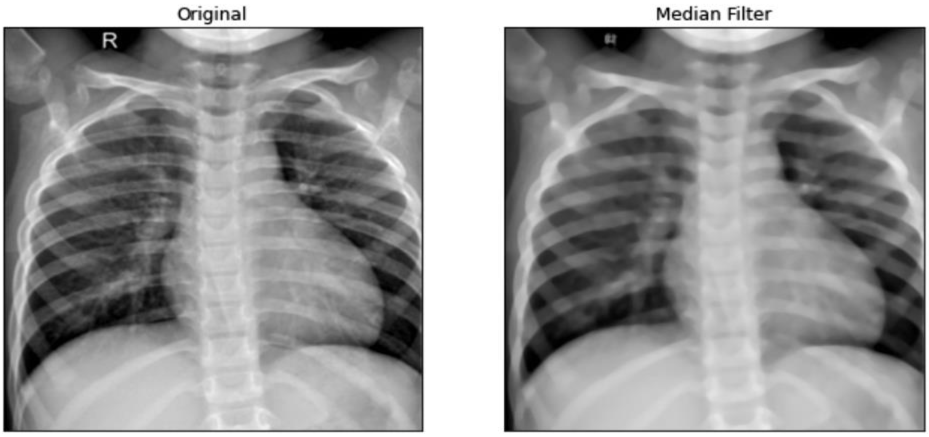


As we can observe that histogram equalization can bring in day night difference when compared to the original image, as it highlights the blacks and whites in the original image.

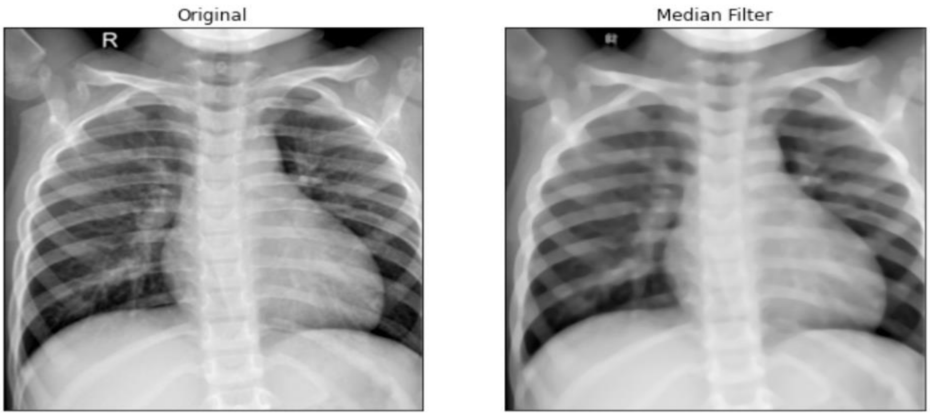
MEDIAN FILTER:

Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. It is particularly effective at removing 'salt and pepper' type noise.

Here we have an image of normal lungs on which median filters has been applied on.



Here we have an image of pneumonia affected lungs on which median filters has been applied on.

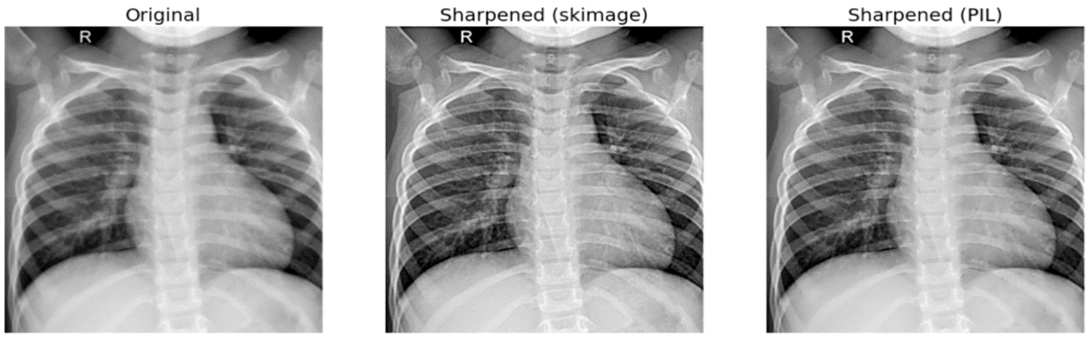


The application of median filter has been effective in removing the salt pepper noise from the original image, the unwanted disturbance has been removed.

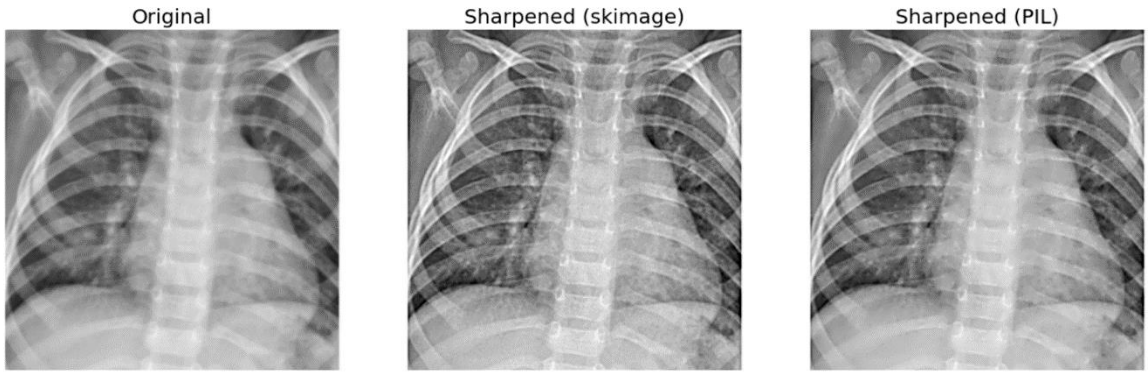
UNSHARP MASK FILTERING:

The unsharp mask filter algorithm is an extremely versatile sharpening tool that improves the definition of fine detail by removing low-frequency spatial information from the original image. Enhancing the overall sharpness of a digital image often has the effect of revealing fine details that cannot be clearly discerned in the original.

Here we have an image of normal lungs on which unsharp masking filters has been applied on.



Here we have an image of pneumonia affected lungs on which unsharp masking filters has been applied on.



The major difference after applying this filtering technique is that we have a more uniformly sharpened image, which brings out the detail in the Rib-cage bones

IMAGE RESTORATION:

Image Restoration is a family of inverse problems for obtaining a high quality image from a corrupted input image. Corruption may occur due to the image-capture process, or photography in non-ideal conditions.

The various types of Image Restorations are:

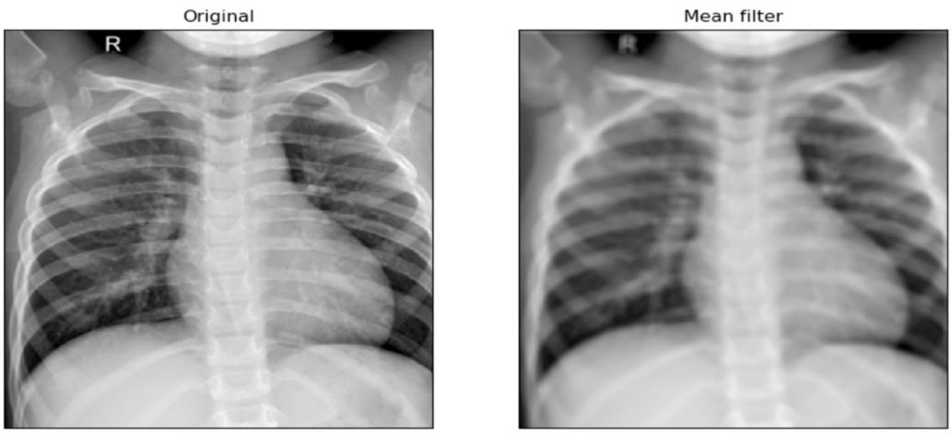
- Gaussian Filters
- Laplacian Filters
- Mean Filters
- Constraint Least-Square Filter
- Wiener Filter
- Direct Inverse Filtering

All of these filters have their own functionalities & features, and so we will be using few of them on the lung images

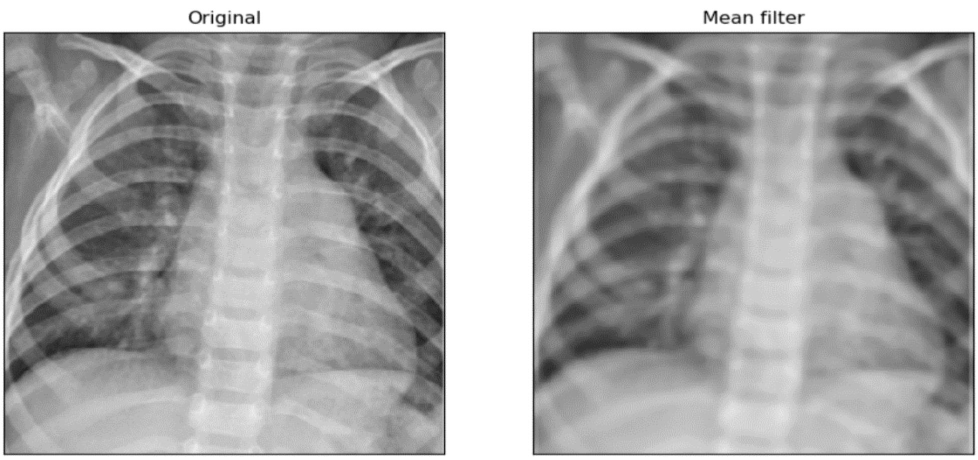
MEAN FILTERS:

Mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e., reducing the amount of intensity variation between one pixel and the next. The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbours, including itself.

Here we have an image of normal lungs on which Mean Filter has been enforced on.



Here we have an image of pneumonia affected lungs on which Mean Filter has been enforced on.

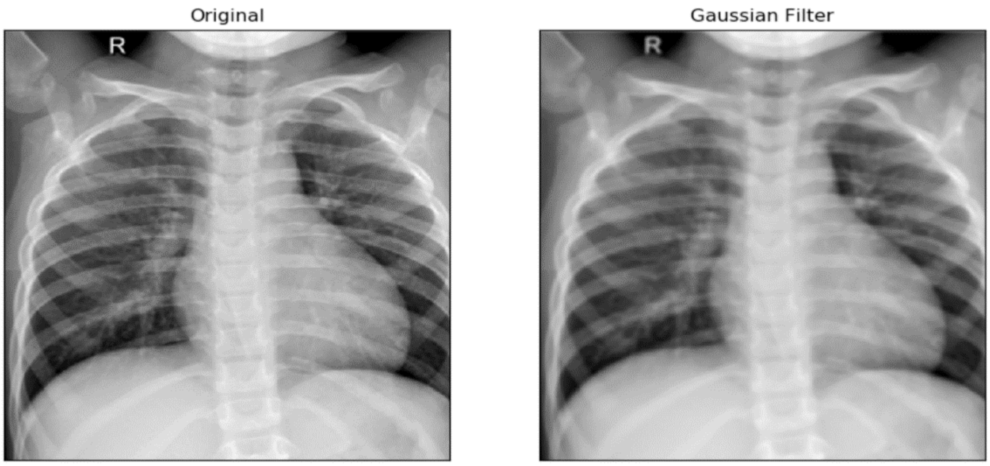


Upon close observation we can notice that it removes the intensity variation between the pixels with variant values

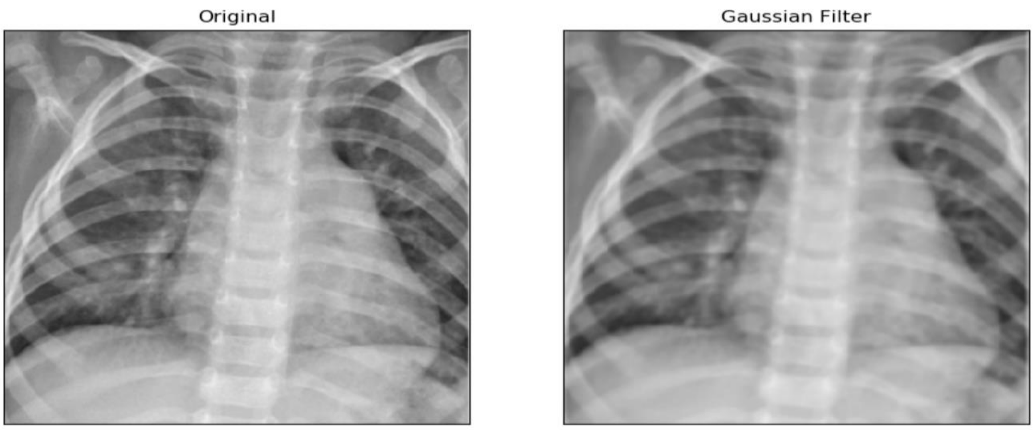
GAUSSIAN FILTERS:

The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove detail and noise. In this sense it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian hump. In 2-D, an isotropic Gaussian has the form:

Here we have an image of normal lungs on which Gaussian Filter has been enforced on.



Here we have an image of pneumonia affected lungs on which Gaussian Filter has been enforced on.

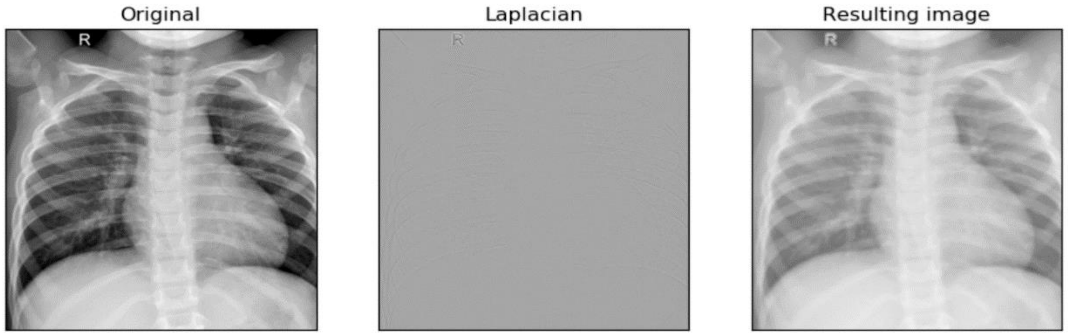


Using Gaussian filtering method we can reduce the noise present in the image, but it also takes away some of the details present.

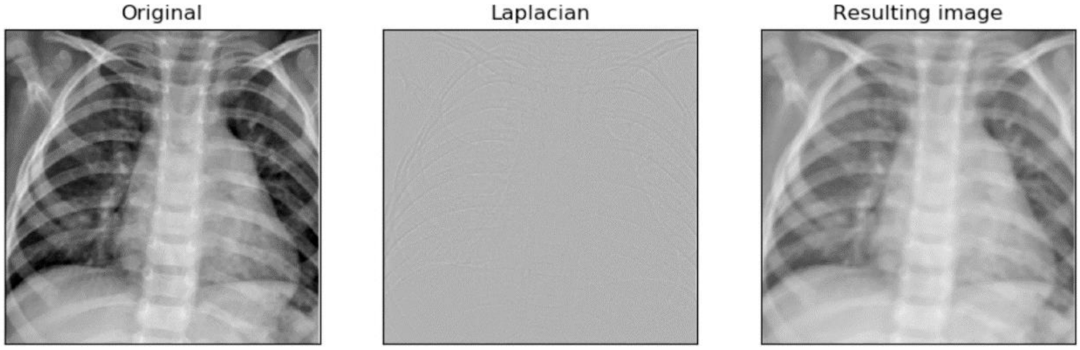
LAPLACIAN FILTER:

The Laplacian filter is an edge detector used to compute the second derivatives of an image, measuring the rate at which the first derivatives change. The Laplacian of an image highlights regions of rapid intensity change and is an example of a second order or a second derivative method of enhancement. This determines if a change in adjacent pixel values is from an edge or continuous progression.

Here we have an image of normal lungs on which Laplacian Filter has been enforced on.



Here we have an image of pneumonia affected lungs on which Laplacian Filter has been enforced on.



This method functions in a slightly different way as it identifies areas or pixels with rapid change in intensity

IMAGE SEGMENTATION:

Image segmentation is a commonly used technique in digital image processing and analysis to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image. Image segmentation could involve separating foreground from background, or clustering regions of pixels based on similarities in color or shape.

The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse.

There are numerous types Image Segmentations:

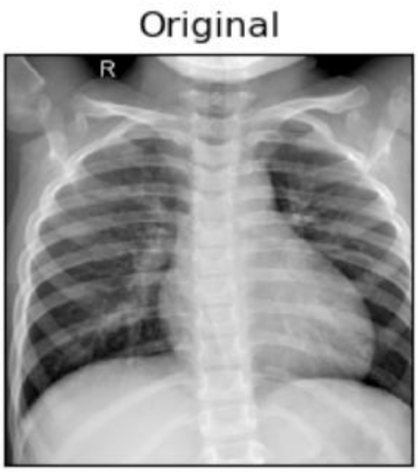
- Threshold Based Segmentation
- Edge-Detection Segmentation
- Region-Based Segmentation
- Watershed Segmentation
- Clustering-Based Segmentation Algorithms

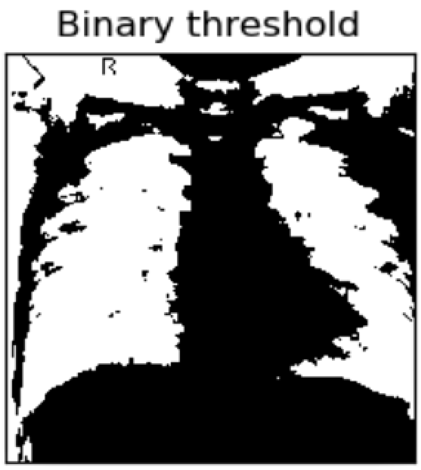
In our project for Image Segmentation, we'll be using few of the above mentioned segmentation types

THRESHOLD BASED SEGMENTATION:

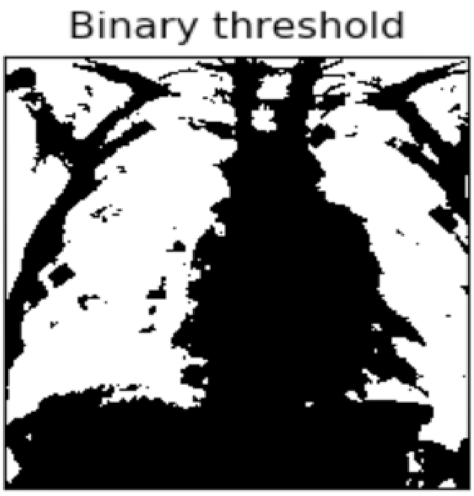
Thresholding is a very popular segmentation technique, used for separating an object from its background. In this method we try different thresholding values and compare and contrast which is the better results. In this method we have to choose appropriate value of T, else we will lose many details in the image.

Here we have an image of normal lungs on which Thresholding segmentation has been enforced on.





Here we have an image of pneumonia affected lungs on which Thresholding segmentation has been enforced on.



EDGE DETECTION SEGMENTATION:

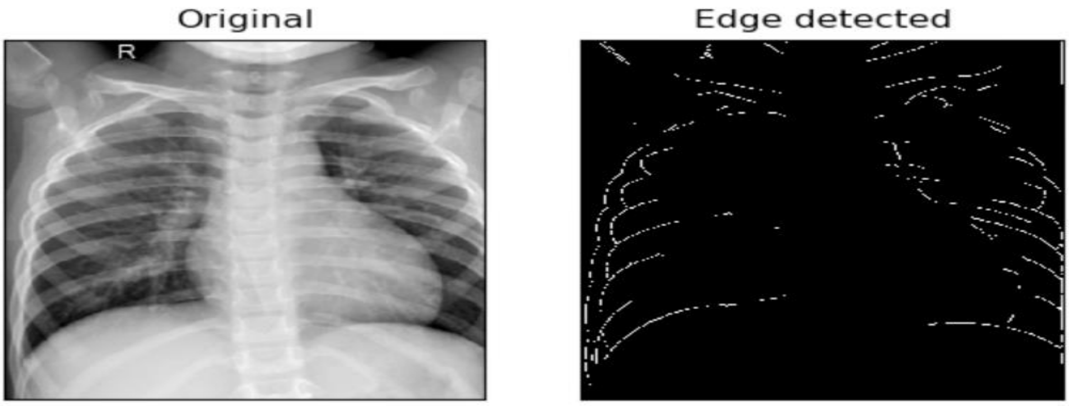
In edge-detection segmentation, an edge filter is applied to the image, pixels are classified as edge or non-edge depending on the filter output, and pixels which are not separated by an edge are allocated to the same category.

The edge based method can be preferable because:

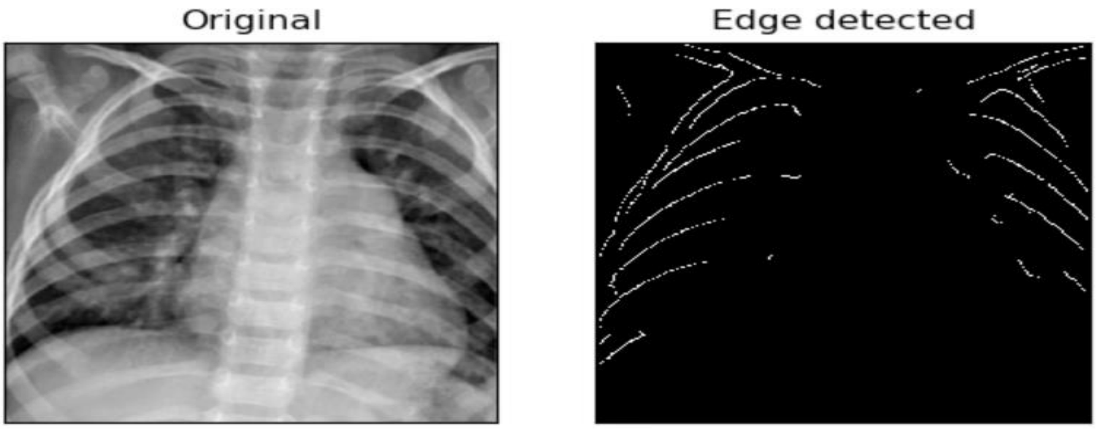
➢ Algorithms are usually less complex

➢ Edges are important features in an image to separate regions

Here we have an image of normal lungs on which Edge segmentation has been enforced on.



Here we have an image of pneumonia affected lungs on which Edge segmentation has been enforced on.



FINAL OBSERVATION:

IMAGE PROCESSING TECNIQUES	BEST FOR OUR PROJECT
IMAGE ENHANCEMENT	HISTOGRAM EQUALIZATION
IMAGE RESTORATION	GAUSSIAN FILTER
IMAGE SEGMENTATION	EDGE DETECTION

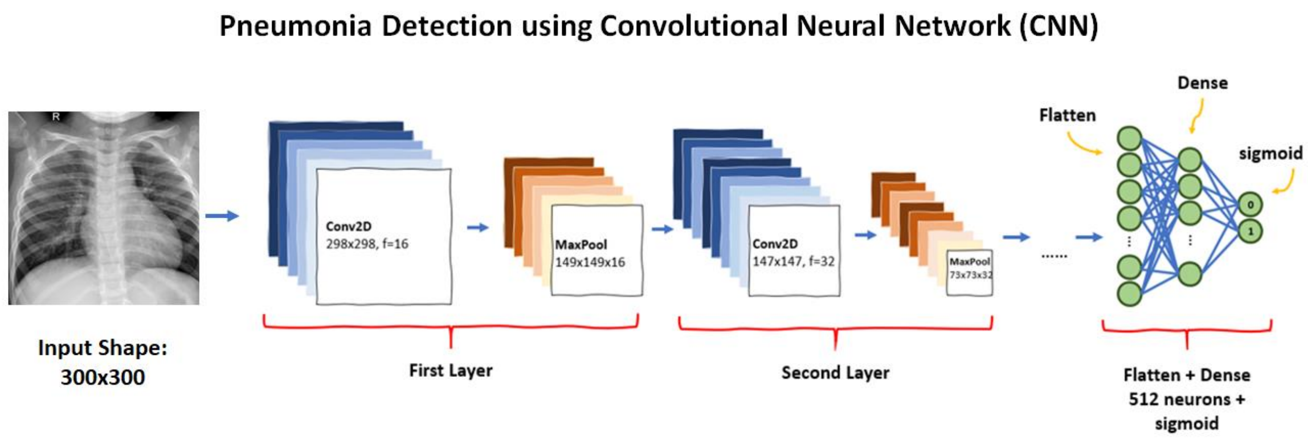
APPROACH:

In our Project We are Using CNN (**convolutional neural network)** algorithm for detecting pneumonia in affected lungs.

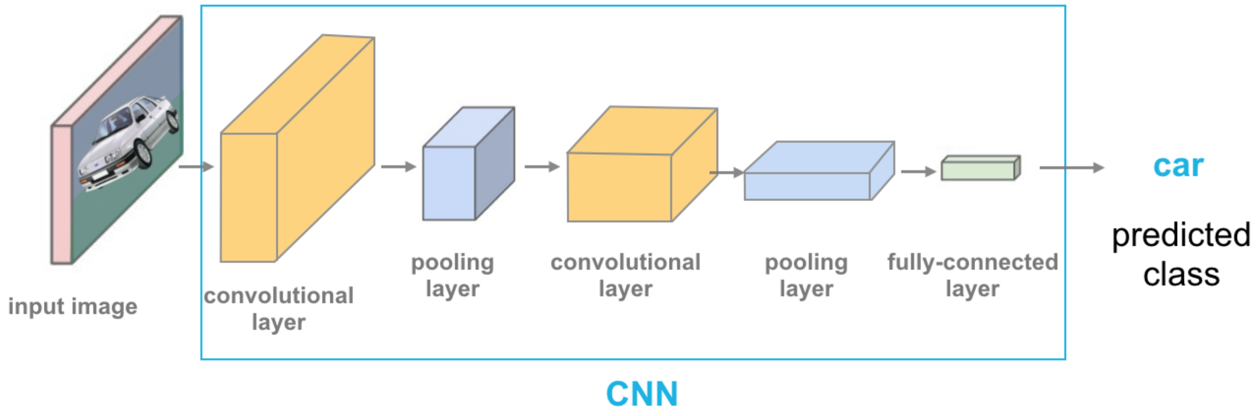
CNN

CNN is a powerful algorithm for image processing. These algorithms are currently the best algorithms we have for the automated processing of images. Many companies use these algorithms to do things like identifying the objects in an image.

Images contain data of RGB combination. Matplotlib can be used to import an image into memory from a file. The computer doesn't see an image, all it sees is an array of numbers. Color images are stored in 3-dimensional arrays. The first two dimensions correspond to the height and width of the image (the number of pixels). The last dimension corresponds to the red, green, and blue colors present in each pixel.



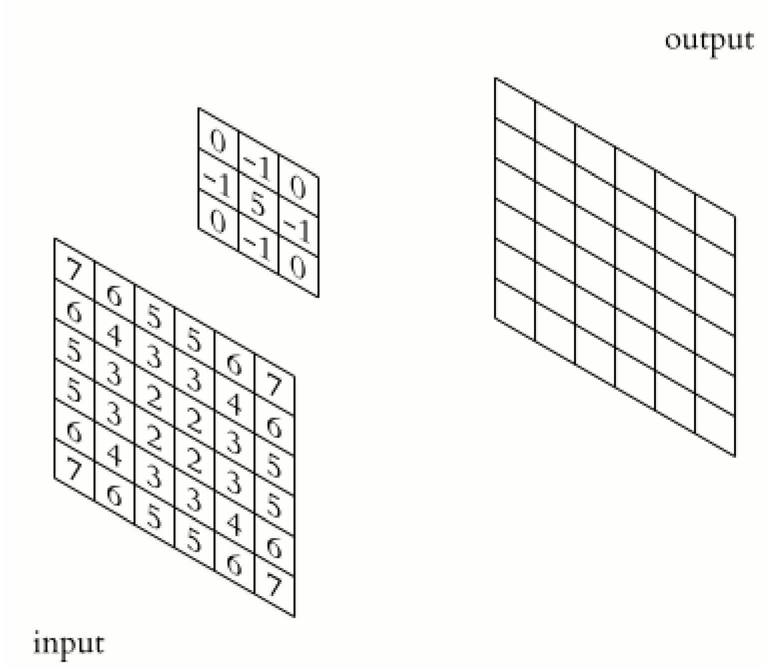
Breakdown of CNN:



Convolution Layer:

In a typical neural network, each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connects to the neuron hidden layer.

After multiplication, the result obtained is called a Feature map, as shown below.



Stride:

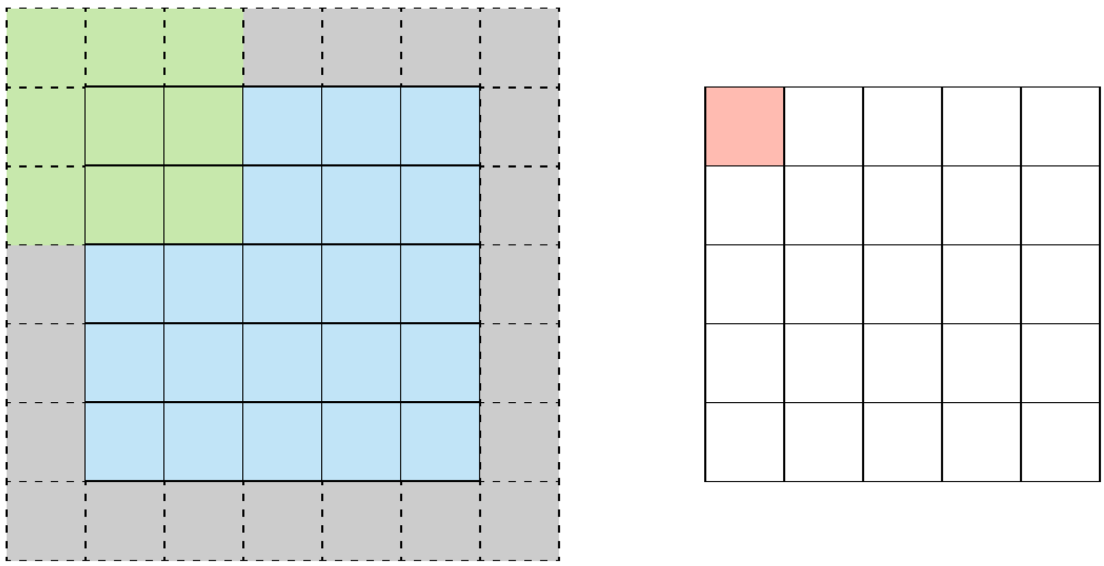
Stride is the number of pixels shifts over the input matrix. When the stride is 1, then we move the filters to 1 pixel at a time.

Padding:

Sometimes, the filter does not fit perfectly fit the input image.

1) Pad the picture with zeros (zero-padding) so that it fits.

2) Drop the part of the image where the filter did not fit. This is called valid padding, which keeps only a valid part of the image



Stride 1 with Padding

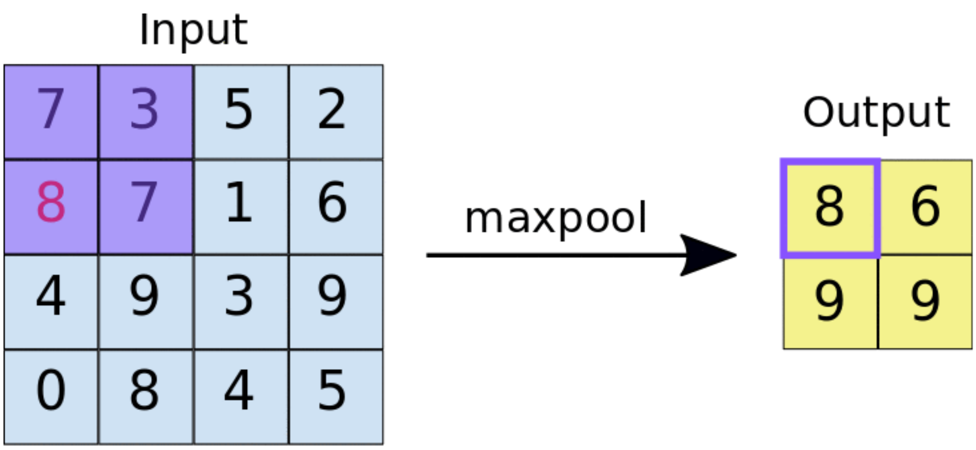
Feature Map

Pooling Layer:

The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN.

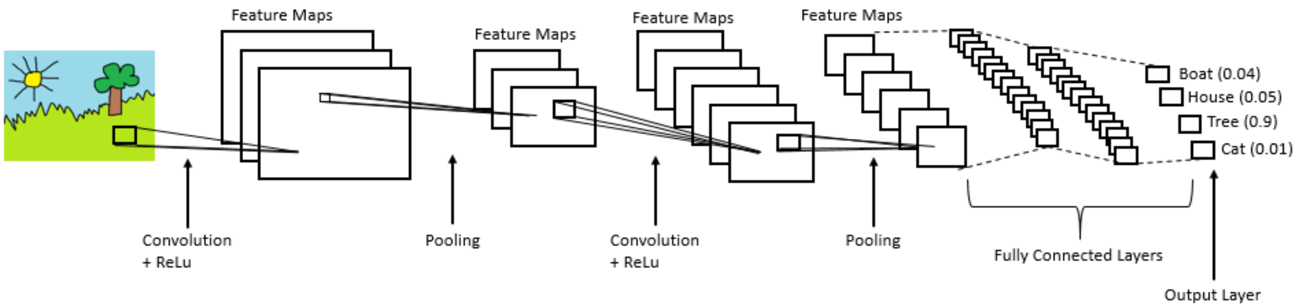
The pooling layer **summarises the features present in a region of the feature map generated by a convolution layer**

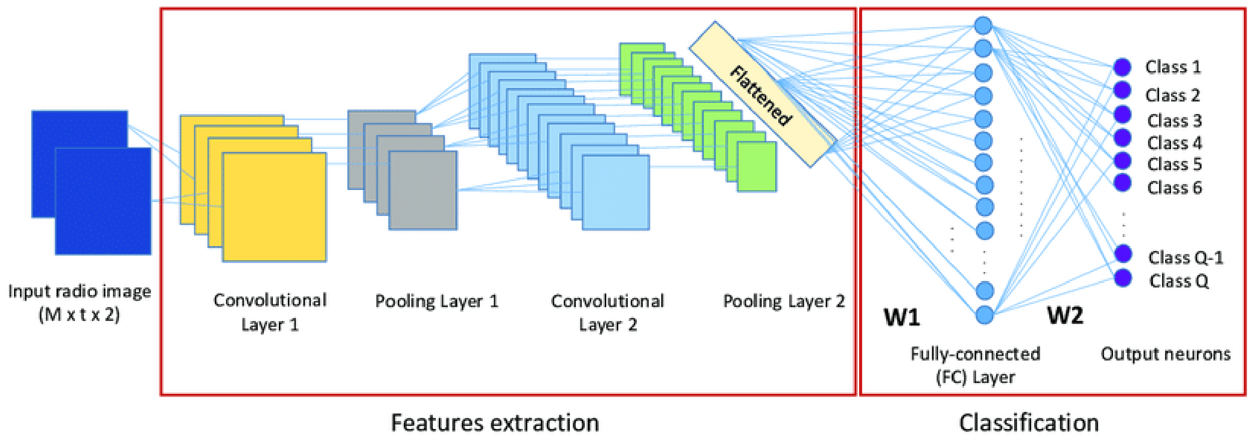
There are several pooling functions such as the average of the rectangular neighborhood, L2 norm of the rectangular neighborhood, and a weighted average based on the distance from the central pixel.



Fully Connected Layer:

Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer





Steps By Step Implementation:

1.Importing Libraries

`Numpy, pandas, matplotlib.pyplot, plotly, random, os, tensorflow, plotly.graph_objs etc.`

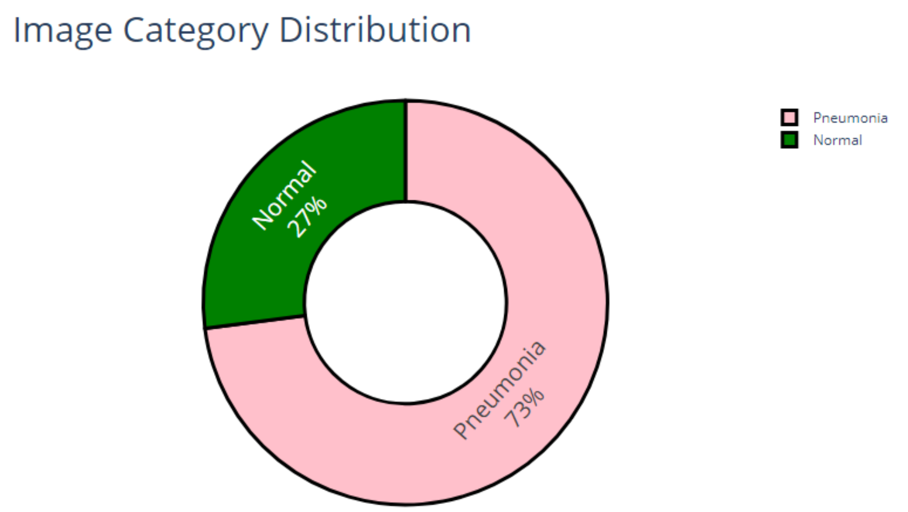
2.Loading Data

We have loaded all the data from Kaggle, then the images are distributed into Training Set, Testing Set and Validation Set. Later on, we obtain images classified as Normal lungs and Pneumonia lungs.

```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Total Pneumonia Images: 4273
Total Normal Images: 1583
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
```

3.Data Exploration

Data exploration is **the first step of data analysis used to explore and visualize data to uncover insights from the start or identify areas or patterns to dig into more**



4.SHUFFLING

After the classified images of Normal and Pneumonia lungs are obtained, they are shuffled using random.shuffle in python, after this we will be performing coding to identify Normal and Pneumonia lungs from the shuffled set and also obtain the exact number of images.

5. X-RAY Conversion

Here,we viewed all shuffled image in X-ray

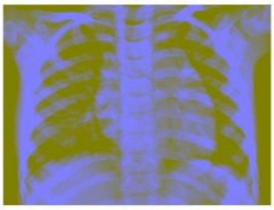
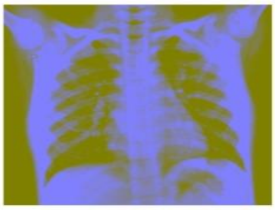
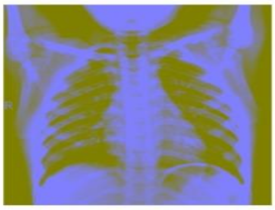
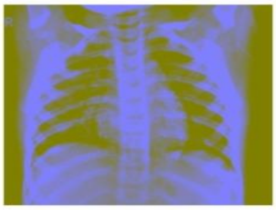


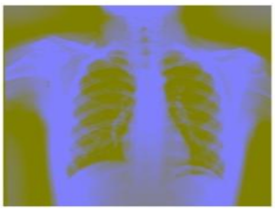
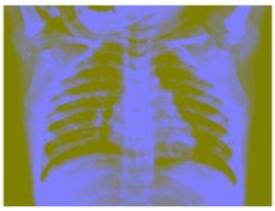
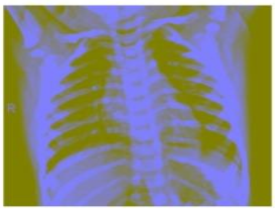
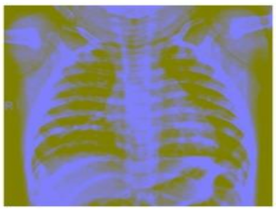

6. Greyscale Demonstration

Here, we convert our x ray images to Greyscale and then apply Gaussian blur to them.

7.Gaussian Filter

As mentioned in the above table we have used Gaussian Filter for Image Restoration.

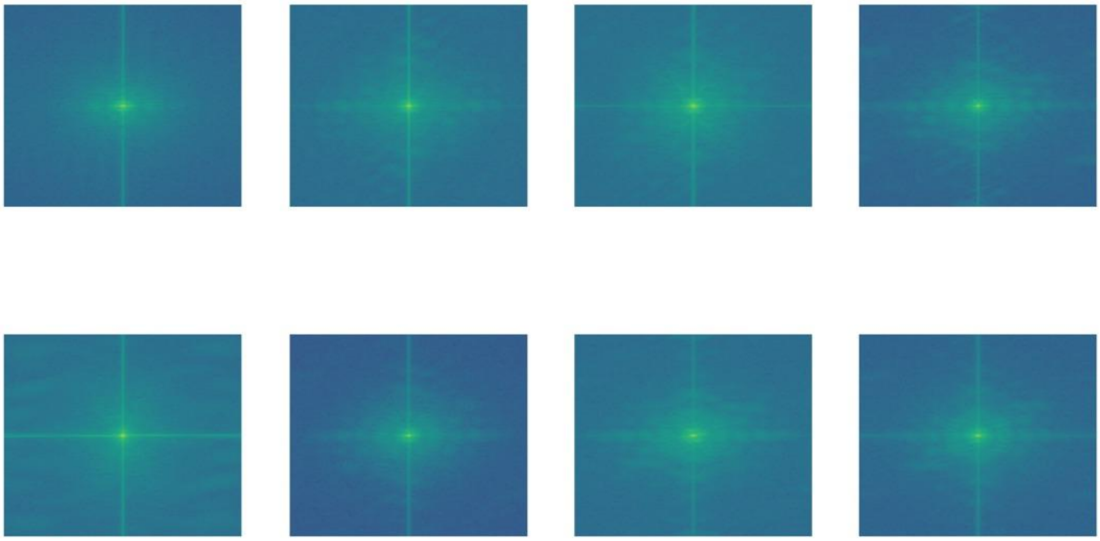





8.Fourier method

Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components

Using Fourier method, we can convert the image from Spatial domain to frequency domain and the following output is obtained.

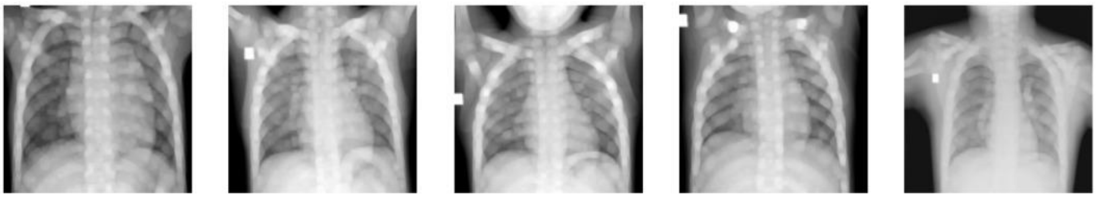


9.Erosion

Erosion removes pixels on object boundaries. Here erosion can strip away extrusions. This will help to remove the imperfection from the segmented image.

10.Dilation

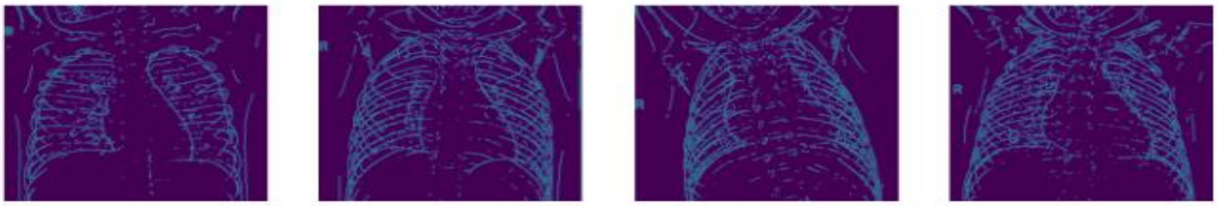
Dilation adds pixels to the boundaries of objects in an image. Dilation has many applications but is most commonly used to exaggerate features in an image that would otherwise be missed. Dilation can repair intrusions.

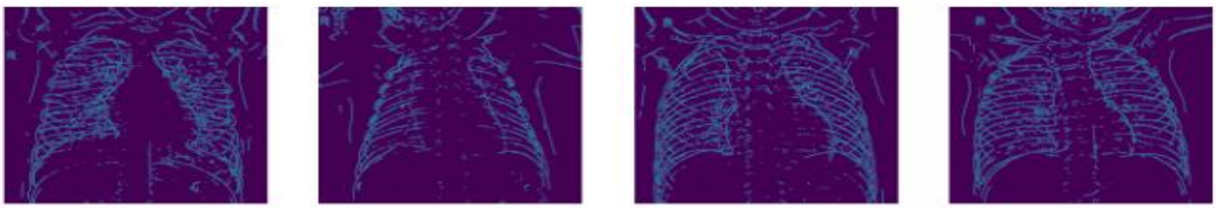


11.Open CV Canny Edge Detection

Canny Edge Detection is a popular edge detection algorithm

By using this Segmentation Technique in OpenCV library, we can perform noise reduction, Finding Intensity Gradient of the Image, Hysteresis Thresholding in one go.





12.Model Building

The model building is done by dividing our data to create a training and validation set using the Keras Image DataGenerator.

By taking training set as input layer we need to ensure that the first layer accepts the exact same shape as the image size. Then, this input layer is connected to several convolution-pooling layer pairs before eventually being flattened and connected to dense layers.

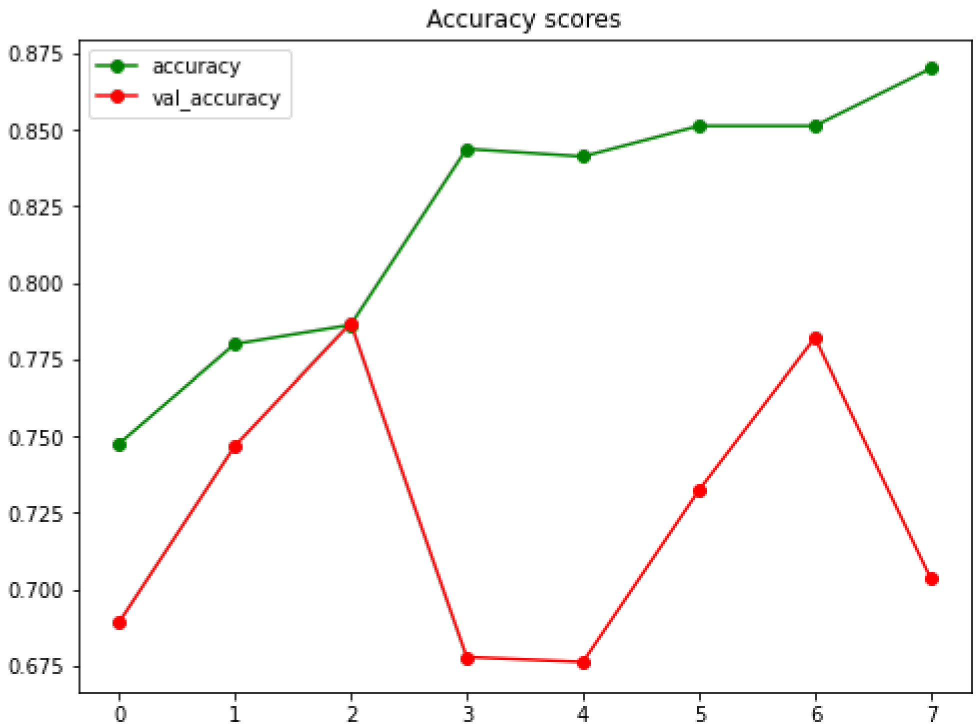
Notice that all hidden layers in the model are using the ReLU activation function due to the fact that ReLU is faster to compute compared to sigmoid, and thus, the training time required is shorter.

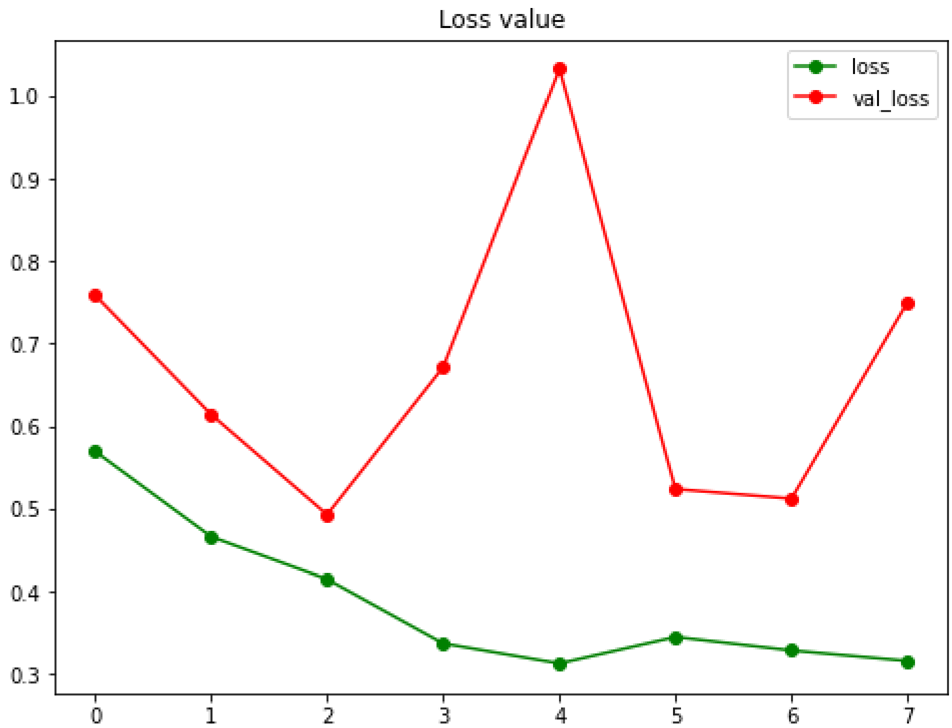
For training the model we are going to use fit_generator() instead of fit() because we are going to take the train data from the train_gen object.

```
Found 5216 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 224, 224, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 112, 112, 32)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 112, 112, 64)      18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 56, 56, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 56, 56, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 28, 28, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 28, 28, 256)       295168
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 256)       0
_________________________________________________________________
flatten (Flatten)            (None, 50176)             0
_________________________________________________________________
dense (Dense)                (None, 128)               6422656
_________________________________________________________________
dense_1 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 130
=================================================================
Total params: 6,819,458
```

Training results are tested against validation set to visualize accuracy and loss data





13.Transfer Learning

Here model developed for a task is reused as the starting point for a model on a **second task. The intuition behind transfer learning for image classification is that if a model is traine**d on a large and general enough dataset, this model will effectively serve as a generic model of the visual world.

We can then take advantage of these learned feature maps without having to start from nothing by training a large model on a large dataset.

a.) VGG16

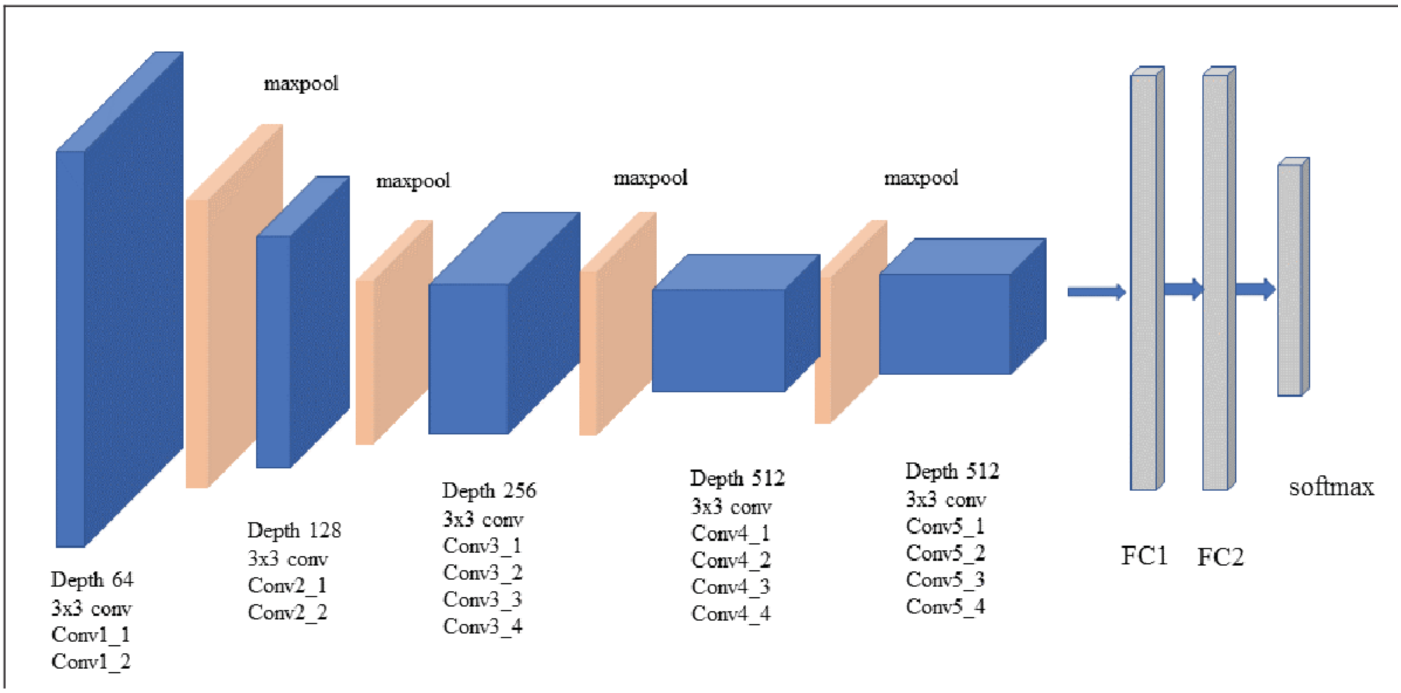


Image Recognition or Classification – VGG16 can be used for disease diagnosis using medical imaging like x-ray or MRI (Magnetic Resonance Imaging). It can also be used in recognizing street signs from a moving vehicle.

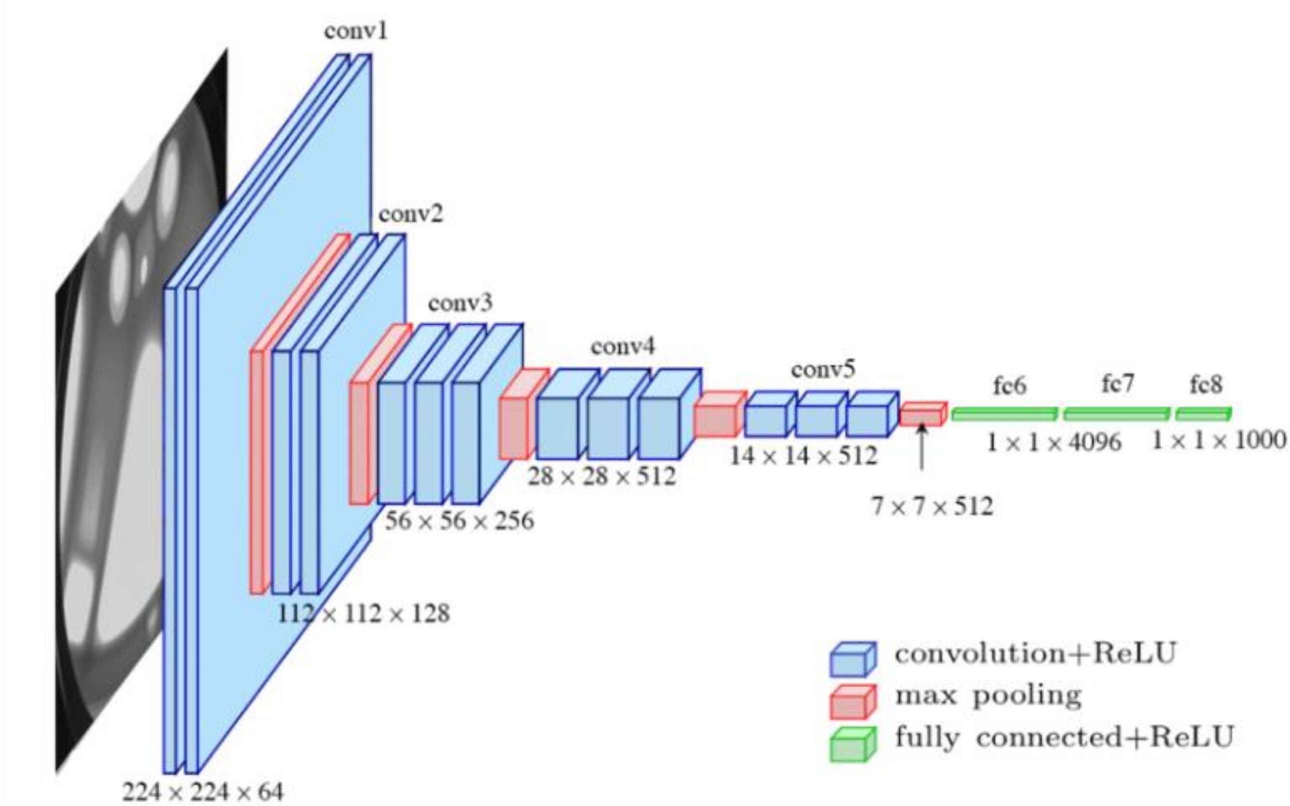
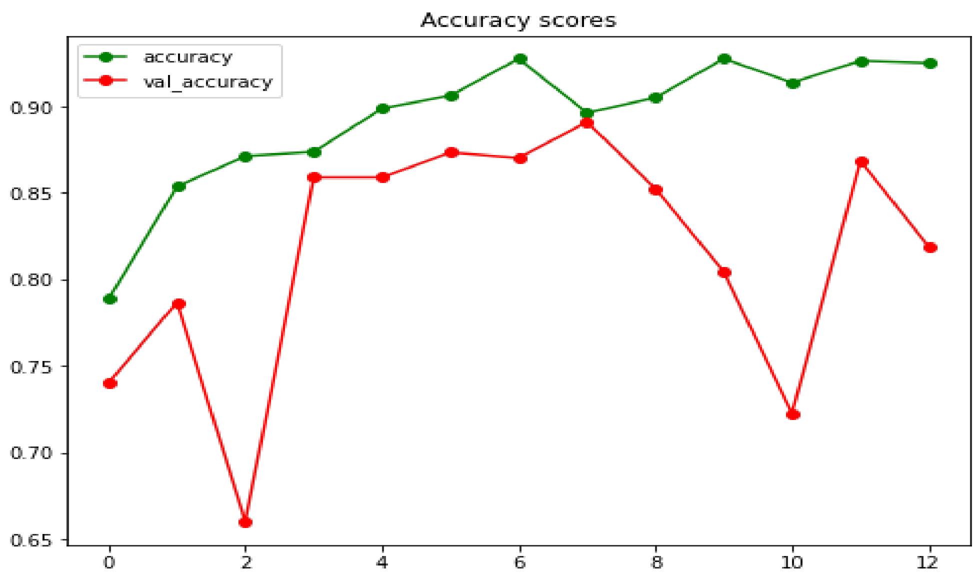
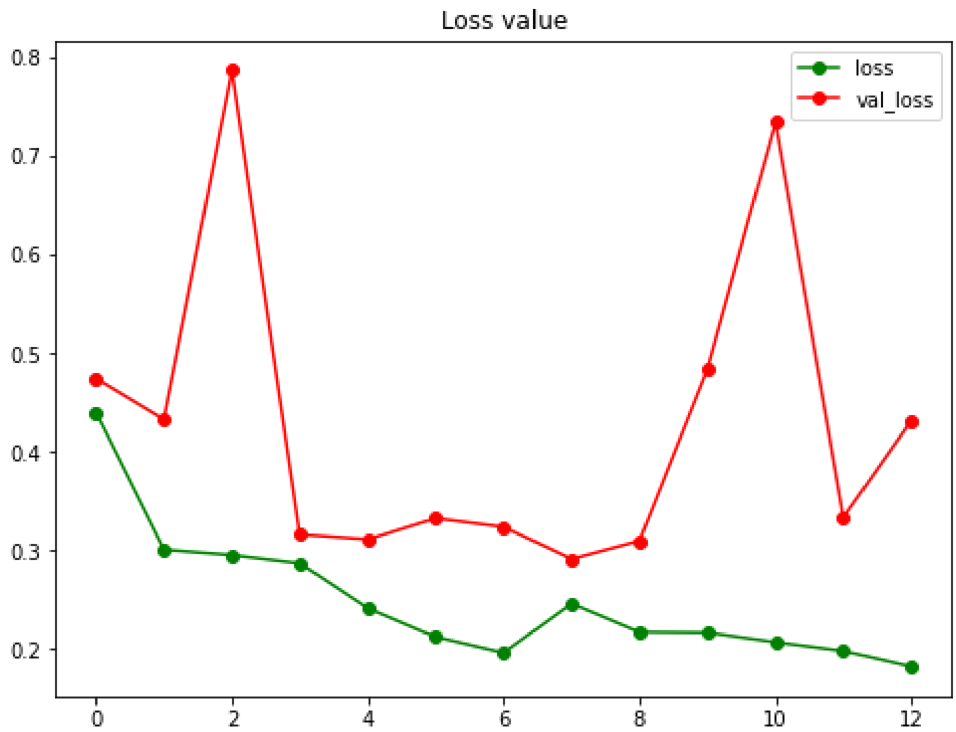


Image Detection and Localization – VGG16 can perform well in image detection use cases.

Image Embedding Vectors – After popping out the top output layer, the model can be used to train to create image embedding vectors which can be used for a problem like face verification using VGG16 inside a Siamese network.





CONCLUSION:

A large number of X-ray images can be processed very quickly to provide highly precise diagnostic results, thus helping healthcare systems provide **efficient patient care services and reduce mortality rates. These convolutional neural** networks' models were successfully achieved by employing various methods of parameter tuning like adding dropout, changing learning rates, **changing the batch size, number of epochs, adding more complex fully connected layers and using transfer learning.**

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