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Evaluating and Selecting Optimal CNN Architectures for Accurate Pneumonia Detection in Chest X-Rays

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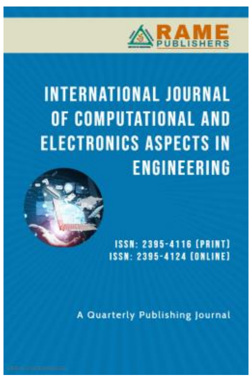

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Abstract- Pneumonia is the lungs' alveoli filling with fluid, and it mainly affects children below 5 years and adults above 65. Results: We demonstrate our approach using different configurations of convolutional neural networks (CNNs) on a chest X-ray binary classification task detecting pneumonia cases. The focus here is more on performance evaluation among various simple CNN architectures to find the one that gives least loss and highest accuracy. The ultimate aim is to enable the widespread adoption of a strong tool for the diagnosis of viral, bacterial and fungal pneumonia as well as community-acquired pneumonia based on chest X-rays only by clinicians.

Keywords: Pneumonia Detection, CNNs, Chest X-rays, ANN, Neural networks

1. Introduction

Pneumonia is a common condition and causes acute respiratory distress, mostly in children and adults over 65 years of age. Infectious agents viral, fungal or bacterial, invade the lung and prompt an inflammatory response that floods bronchioles and alveoli with fluid making it difficult to breathe. Pneumonia accounted for 15% of deaths among children under five in total all over the world, causing more than an estimated 920,000 fatalities globally in the last year. Pneumonia caused over half a million emergency hospital admissions in the United States and claimed 50,000 lives that year, one of the top ten causes of death in this country [1].

The main categories are community-acquired pneumonia, viral pneumonia and bacterial pneumonia. Community-acquired pneumonia (as opposed to hospital-acquired) causes about 1.5 million U.S. hospitalizations each year [2], [3] It is estimated that viral pneumonia affects 200 million people annually worldwide, equally among adults and children. The bacterial pneumonia, on the other hand is classified into typical and atypical groups; The former's causative bacteria identifiable by Gram stain as well grow in standard media (while their counterpart does not) [4].

The bumper is the Chest X-Rays (CXR), which are used to diagnose pneumonia because they show areas of increased opacity in the lungs, presumably due to alveolar fluid. EOS can be challenging to diagnose due to the other pathologies such as pulmonary edema in congestive heart failure lung cancer, hemmorage from an internal source and atelectasis (deflated areas of lungs) often cause similar imaging findings.

Despite these diagnostic difficulties, machine learning has made great strides in medical imaging. This paper investigates deploying deep learning — a category of machine learning that uses convolutional neural networks (CNNs) built off normal and pneumonia-affected CXR images. We hope to build a high-performance model forpredicting whether new CXRs contain changes that indicate the presence of pneumonia, which would be usefulfor clinical diagnosis in this challenging disease [5].

2. Related works

Medical diagnostics: In the medical domain, a number of studies have investigated classification of chest X-ray images into various pathological categories. We used them to detect pneumonia in the images supported by deep learning models. One major success in this area was achieved by training a 121-layer CNN to classify chest X-ray images (outperforming practicing radiologists), and that could also detect another 14 diseases. It was state-of-the-art and designed to improve the provision of healthcare. [6]

In another study, an attention-guided CNN (AG-CNN) was developed to detect thorax diseases from chest X-ray images, utilizing a dual-branch system to capture both global and local image cues, significantly outperforming existing models with its diagnostic accuracy. Further research in this field extended to the classification and segmentation of brain tumor images using CNNs, demonstrating high accuracy through techniques like data augmentation and feature pooling.[7]

Additional efforts included the development of a dual CNN to automatically recognize images from both frontal and lateral chest X-rays, improving disease detection accuracy through data augmentation and pixel normalization. Deep CNNs were also trained to classify pulmonary tuberculosis from chest radiographs, achieving remarkable diagnostic accuracy [3], [8].

Further explorations involved the identification of interstitial lung disease patterns using a CNN model with a notable accuracy. Transfer models have been adapted for classifying Alzheimer's disease, showcasing the flexibility of deep learning approaches. The versatility of deep CNNs has been further exemplified in incremental learning models for Alzheimer's disease detection, employing cortical thickness data for high specificity, and in innovative approaches to network design that introduced small kernel-sized filters sequentially.[9]

These studies collectively underline the potent capabilities of deep CNN models to deliver groundbreaking results in complex medical image datasets, fundamentally altering the diagnostic processes and enhancing the quality and accuracy of medical imaging diagnostics.[10]

Table 1: Summery of related works

NO	**Focus**	**Model/Technique**	**Dataset**	**Key Findings**
[21]	Thorax disease detection from chest X-rays	GoogLeNet, ResNet-18, and DenseNet-121	RSNA dataset from a Kaggle challenge	Ensemble model outperformed state-of-the-art methods in pneumonia detection accuracy
[14]	Classification of pulmonary tuberculosis from chest radiographs	ReLU activation, dropout, CNN	RSNA pneumonia challenge dataset with normal and non-COVID pneumonia images	CNN model detects COVID-19, bacterial, and viral pneumonia with 95% accuracy
[17]	Detection of Pneumonia using deep learning models from X-Ray images	ResNet-34 based U-Net and EfficientNet-B4 based U-Net.	Kaggle dataset with 5863 Chest X-Ray Images in jpeg format	CNN model designed from scratch for Pneumonia classification
[1]	Detection of pneumonia using pre-trained CNN models for chest X-Rays.	CNN models for image classification	ChestX-ray14 dataset with 112,120 images labeled with 14 diseases	Proposed model architecture for pneumonia detection using DenseNet and SVM
[5]	ImageNet classification challenge	Data augmentation	Pneumonia dataset used in the study	VGG16, VGG19, and a custom CNN model show high accuracy

[12]	Visualization of features in CNN layers for pneumonia detection	CNN model processed using gradient descent algorithm.	Chest X-Ray Images - Kaggle dataset with normal and pneumonia classes	CNN 35 layer: Sensitivity 95.1%, specificity 98.5%, accuracy 96.3%
[15]	Pixel-wise segmentation of chest radiographs	Activation functions ReLU and softmax	MIMIC-CXR dataset for thorax disease detection	Developed CNN models to detect pneumonia with high accuracy.

3. Methods

In this section we briefly describe the methods used to classify a given chest X-ray image (CXR) as positive or negative for pneumonia. It also explains the dataset used, and tools or frameworks that aided our experiments (with all details). The section structure is as follows: Dataset Usage Image Augmentation, (ANN) and (CNN). [11], [12]

3.1. Dataset

The dataset I used can be found in Kaggle by the name "RSNA Pneumonia Detection EDA". The dataset is 3.68 GB in size and provides you with a total of 26684 images meant for training, along with another set containing around 3000 testing samples. This dataset consists of 64X64 grayscale images. We cover three image types: Normal, Lung Opacity and No Lung Opacity / Not Normal [13].

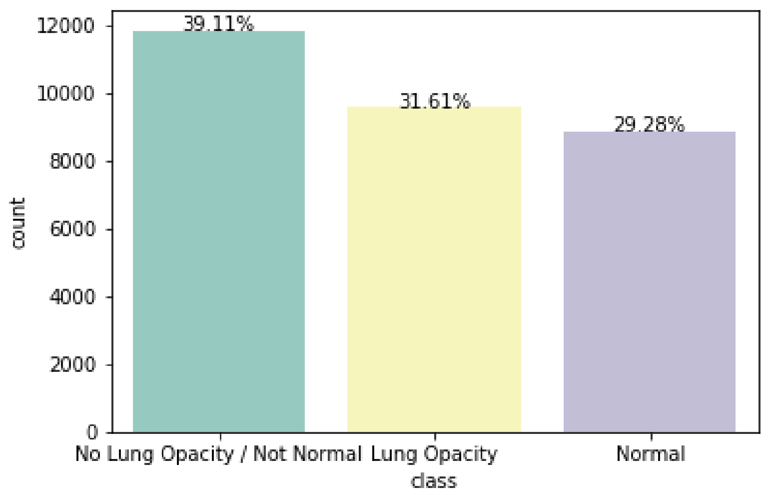


Figure 1 : Ovreview of Dateset Test

3.2. Image Augementation

Deep learning models, particularly Convolutional Neural Networks (CNN), typically require vast amounts of data to train effectively. However, gathering such extensive datasets can be challenging. To address this issue, a technique called image augmentation is employed. This method significantly expands the size of an existing dataset by applying various transformations, such as standardizing pixel values, applying whitening transforms, and performing random rotations, shifts, flips, rescaling, shearing, and zooming. In our process, we use techniques like rescaling, shearing, zooming, and horizontal flipping to diversify and augment the training data.[12], [13], [14], [15].

Figure 2 : X-Ray Augementation

3.3. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs), the foundation of deep learning, are powerful models used in various applications like regression, classification, and specialized tasks like character and speech recognition. An ANN consists of interconnected layers—input, hidden, and output where each layer's nodes are connected through weights adjusted during training. [16]Mathematically, an ANN can be represented by sets of layers (L), nodes (N), and weights (W). The output of each node is calculated by summing the weighted inputs from the previous layer and applying an activation function (e.g., sigmoid, ReLU, softmax) to introduce non-linearity. ANNs are trained through forward propagation of input data, error calculation, and backpropagation to adjust weights for improved accuracy. For instance, Figure 2 depicts an ANN with a layer configuration of {12, 10, 10, 10, 2}, featuring 12 input nodes, 3 hidden layers with 10 nodes each, and 2 output nodes using a softmax activation.[17], [18]

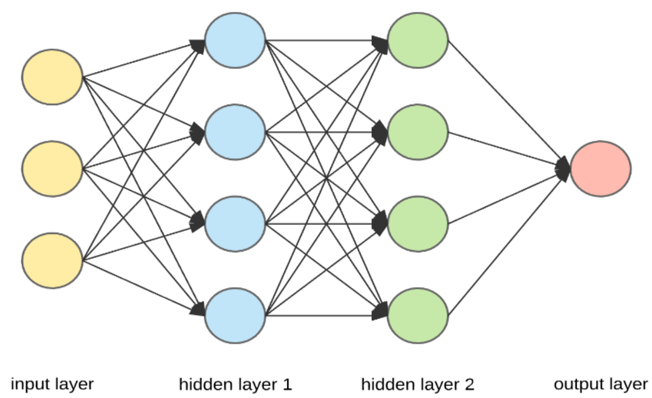


Figure 3 : (ANN) Artificial Neural Network

3.4. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a specialized neural network designed for processing structured grid data, like images. It typically consists of convolutional layers, pooling layers, and fully connected layers.[19][20][21]Convolutional layers use learnable filters to convolve across the input data, creating feature maps, with the output computed as

$$S(i,j) = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} I(i+m, jn) K(m,n)$$

An activation function, such as ReLU f(x)=max(0,x) introduces non-linearity. Pooling layers, often using max pooling, reduce spatial dimensions, calculated as

$$p(i,j) = max_{0 \le m < p, 0 \le n < p}\, S(i.p+m, j.p+n)$$

Fully connected layers at the end integrate features and produce the final output

$$y = f(\sum_{i=1}^{N} wixi + b)$$

This structure allows CNNs to effectively capture spatial hierarchies in data for tasks like image classification.

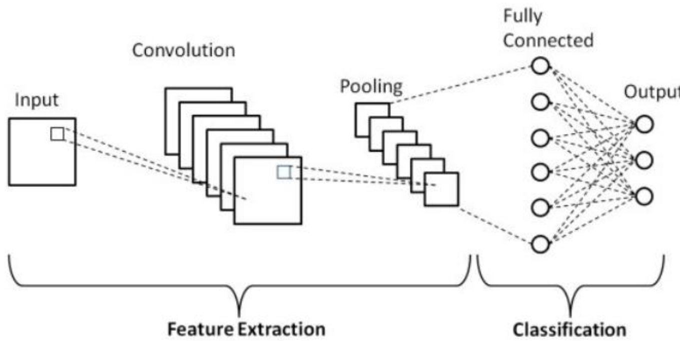


Figure 4: Architecture of a 2 layered CNN

3.5. Software and hardware

All the CNN architectures were trained using Python 3 and the Keras library, which operates on the TensorFlow backend. The high-level API provided by Keras was utilized for constructing and managing the neural networks.[23] The training and experimentation were conducted on a workstation equipped with an Intel i7 10th generation processor and 24 GB of RAM.

4. Experimentation and Results

We demonstrate the experiments on RSNA dataset using different architectures to find out which architecture is compatible for classification in this section. 4.1 This portion is classified into two sections; Experiments and Analysis, 4.2 Selected Architecture Results.

4.1. Experiments and analysis

Experiments were performed on different CNN architectures, by varying the number of convolutional and dense layers as well including or excluding regularizations like L1,L2,BatchNorm and Dropout. We also changed the size of input image, kernel and matrices. We used the maximum accuracy and minimum cross entropy loss during training performance as a metric to measure each architecture.[25]

Table 2 shows results for maximal accuracy loss, minimum loss end training timings out of 15 architectures. In particular, every ANN layer had 128 nodes,in each of the architecture (except for output layer having 2 node). Figures 4 and Figure 5 display the performance statistics, accuracy (left), loss per epoch.

Architectures 10 and 11 performed poorly, likely due to the application of L1 regularization, which hindered the model's ability to learn effectively. We observed that larger architectures generally required more training time, particularly influenced by the input size. However, the training time did not correlate directly with better performance in terms of accuracy or loss reduction.From our analysis, simpler architectures proved more effective, avoiding the risk of underfitting by not detecting non-existent features. Based on the metrics, including maximum accuracy (MVA), least cross-entropy loss (LVCEL), and training time (TT), we selected architecture 5 as the most suitable model for further evaluation on the RSNA dataset.

Table 2: Performance of different CNN architectures

No.	CL	AL	Regularizations	IS	FD	KS	PS	LVCEL	MVA	TT
			L1	L2	BN	DO				
1	2	3	✗	✗	✗	✗	-128,128	{64,32}	{9,3}	{4,2}
2	2	4	✗	✗	✗	✗	-128,128	{64,32}	{9,3}	{4,2}
3	2	4	✗	✗	✓	✓	-128,128	{64,32}	{9,3}	{4,2}
4	2	4	✗	✗	✗	✓	-128,128	{64,32}	{9,3}	{4,2}
5	2	4	✗	✗	✗	✗	(64,64)	{64,32}	{9,3}	{4,2}
6	2	4	✗	✗	✗	✗	(64,64)	{64,32}	{9,3}	{4,2}
7	2	3	✗	✗	✓	✓	-128,128	{64,32}	{9,3}	{4,2}
8	3	4	✗	✗	✓	✓	-128,128	{128,64,32}	{9,6,3}	{4,2,2}
9	3	5	✗	✗	✗	✓	-128,128	{128,64,32}	{9,6,3}	{4,2,2}
10	4	4	✓	✗	✗	✗	-128,128	{128,64,32,16}	{9,6,3,3}	{4,2,2,2}
11	4	5	✓	✗	✗	✗	-128,128	{128,64,32,16}	{9,6,3,3}	{4,2,2,2}
12	4	5	✗	✗	✓	✗	-128,128	{128,64,32,16}	{9,6,3,3}	{4,2,2,2}
13	4	5	✗	✗	✗	✗	(64,64)	{64,32,32,16}	{9,6,3,3}	{2,2,2,2}
14	5	5	✗	✗	✓	✓	-128,128	{128,64,64,32,16}	{9,6,6,3,3}	{2,2,2,2,2}
15	5	6	✗	✗	✗	✗	-128,128	{128,64,32,16}	{9,6,3,3}	{2,2,2,2,2

Table 3 : Abbreviations used in Table 2

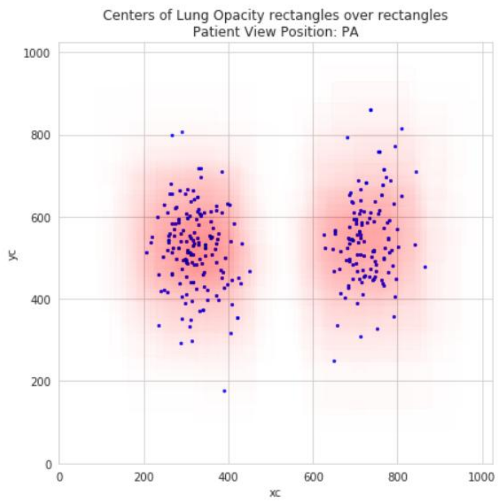
Abbreviation	Meaning
CL	Convolutional Layers
AL	Additional Layers
Regularizations	
L1	L1 Regularization
L2	L2 Regularization
BN	Batch Normalization
DO	Dropout
IS	Input Size
FD	Filter Dimensions
KS	Kernel Size
PS	Pooling Size
LVCEL	Least Cross-Entropy Loss
MVA	Maximum Accuracy
TT	Training Time (seconds)

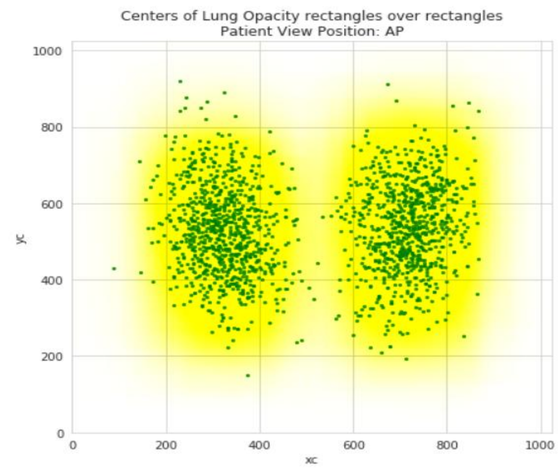
4.2. Results of selected architecture

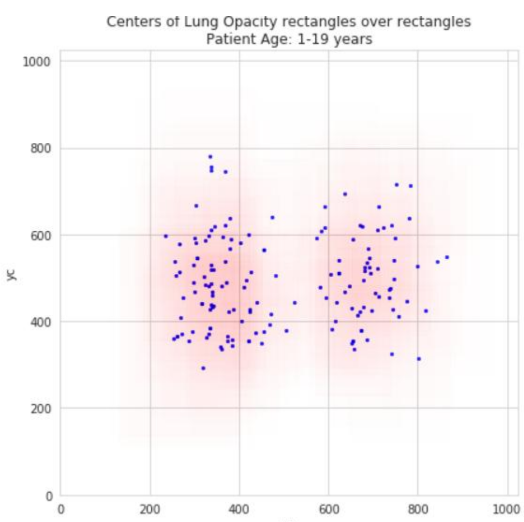
We assess the model performance using evaluation metrics based on two body positions present in the dataset: AP (Anterior/Posterior) and PA (Posterior/Anterior). The definitions of these view positions are as follows:

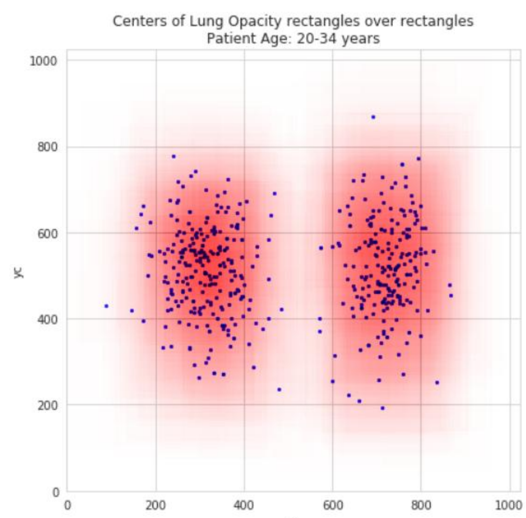
Table 4 : Dataset Accurecy

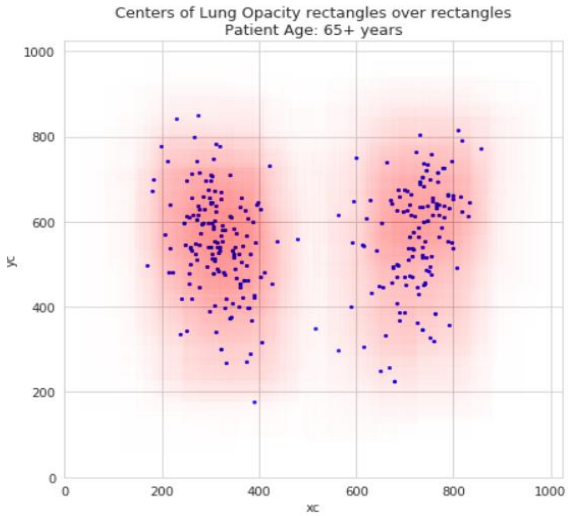
Feature	View Position
AP	21,817 or 57.97%
PA	15,812 or 42.02%

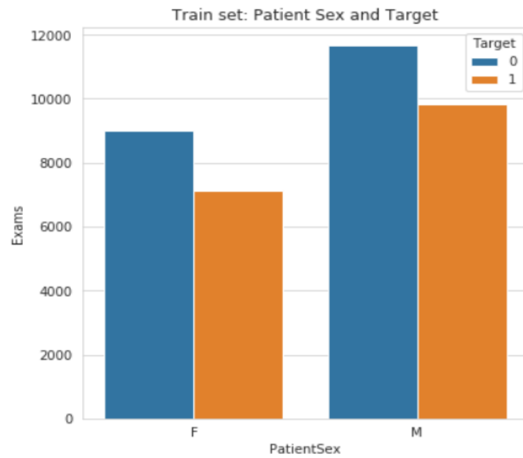


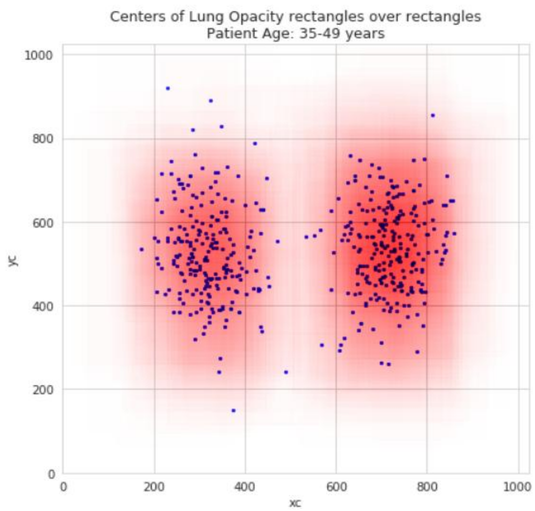


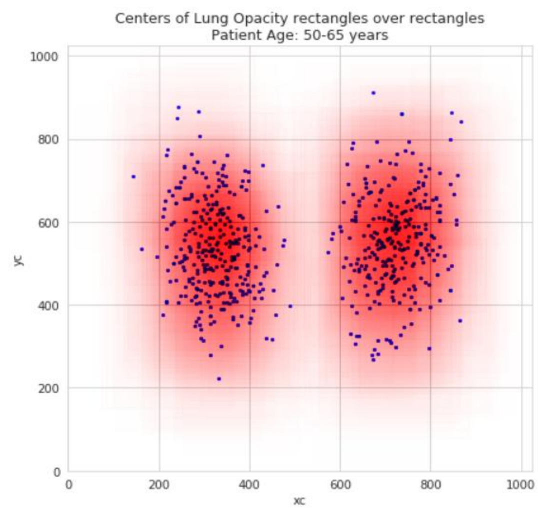


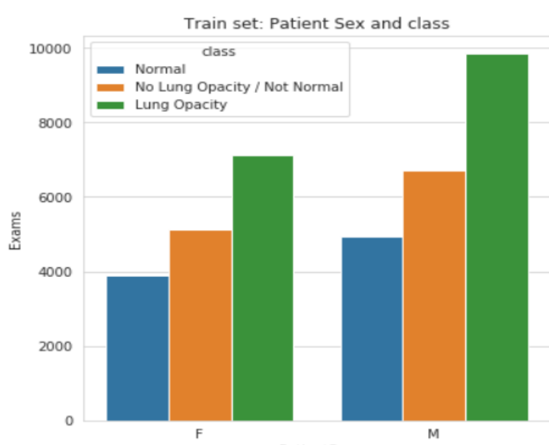


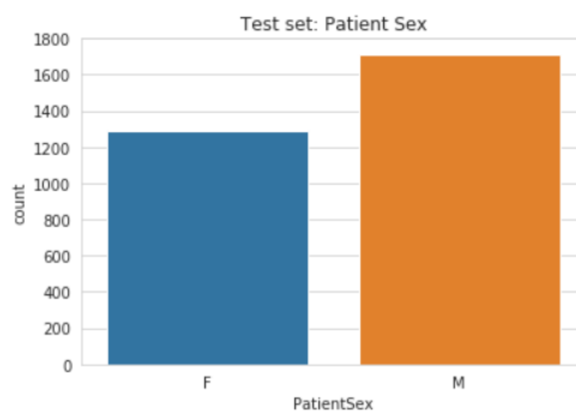

Centers of Lung Opacity rectangles over rectangles
Patient Age: 65+ years
yc
xc


Train set: Patient Sex and Target
Target
0
1
Exams
F
M
PatientSex


Centers of Lung Opacity rectangles over rectangles
Patient Age: 35-49 years
yc
xc


Centers of Lung Opacity rectangles over rectangles
Patient Age: 50-65 years
yc
xc


Train set: Patient Sex and class
class
Normal
No Lung Opacity / Not Normal
Lung Opacity
Exams
F
M
PatientSex


Test set: Patient Sex
count
F
M
PatientSex

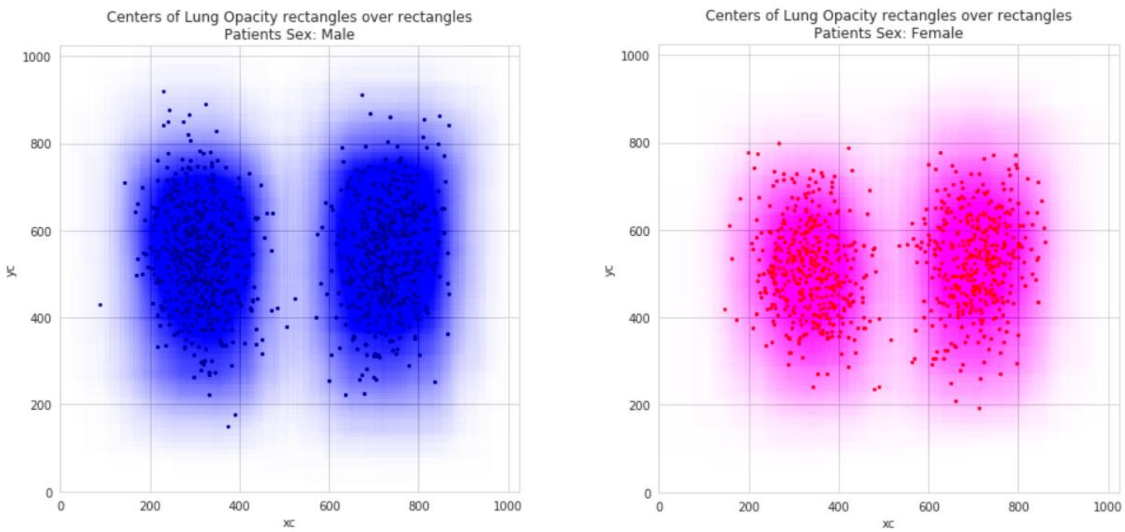


Figure 5. Model performance using evaluation metrics

5. Conclusions

We compared the performance of 15 different CNN architectures that were trained on identical datasets, to identify a less complex method for pneumonia detection from chest X-rays in this study. Given our findings, we choose the most adequate model that is computationally efficient with out losing in interpretability while still bringing strong performance metrics. The accuracy and quality of the proposed architecture in this study are competitive with state-of-the-art models, demonstrating that simple CNN can reader more complexity as well as maintaining interpretability. From what we observed in our work, we recommend digging deeper into tuning down simpler architectures to perform even higher. We have a strong feeling that the architecture we selected (Model 5) may likely give even better performance given further tuning and trial/error. Multimodal learning that includes both patient symptoms as text and CXR images could be explored in future work for better diagnosis.

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