Assignment 1- Contributions

We [Smitesh Patil, Ambuj Mittal, Dhruv Solanki] worked together on this study 'Critical Review on Deep Learning for Medical Image Segmentation based on X-Ray Images',

Three of us went through each of the 8 research papers mentioned in the literature and each of us came up with the initial write-up for the paper. Then, we collated the writeup to prepare the final draft. Ambuj formatted the write-up and generated the IEEE format using latex. Smitesh did the comparison part with the table in the research paper generated using R.

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Critical Review on Deep Learning For Medical Image Segmentation based on X-Ray Images

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***Abstract*—Pneumonia is the inflammation of lung tissue caused by many factors like viral or bacterial infection and is mostly detected by medical imaging technique using X-Ray images. It is estimated that 2.5 million people die each year of pneumonia [1]. Deep Learning based models are regularly used for medical image segmentation. In this paper, we are have carried out a review of various research papers on implementation of deep learning models developed by researchers who have based their models on Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) for detecting pneumonia using X-Ray image segmentation.**

***Index Terms*—Pneumonia, Deep Learning, CNN, RNN, LSTM, Medical Image Segmentation, Review**

I. Introduction

Among many benign and harmful lung diseases known to humankind, Pneumonia is one the most infectious lung diseases that is caused by plethora of dangerous microorganisms like bacteria, fungi, viruses, and some parasites as well. The main characteristic of an infection that is caused due to pneumonia is inflammation of lung tissue of the tiny air sacs in the lungs called alveoli. The patient suffering from pneumonia may encounter symptoms that range from mild fever, coughing to severe chest pain and difficulty in breathing.

The diagnosis of Pneumonia is carried out by combining physical examination and various diagnostic tests like blood sampling, Chest X-Ray (CXR), sputum culture, Bronchoscopy [2]. The most relevant diagnostic test for identifying the severity of pneumonia is a Chest X-Ray (CXR). A CXR generates an image of the chest of the patient which can be used to check the signs for pneumonia patches, fluid inside the lungs, and an augmentation of lung tissue density.

In digital image processing, image segmentation is the process of identifying certain recurring patterns in a set of images. In the specific case of Medical Image Segmentation, medical image data formats like X-rays are used to identify certain aspects of the image like tumours, organ defects, etc as per the target of the study undertaken. A lot of research has been done in Medical Image Segmentation to automate the identification of pneumonia patches using various deep learning techniques.

This has motivated us to write an article reviewing these techniques developed by researchers, compare them, and suggest improvements to the architecture and approach to this problem. The rest of this paper is organised as follows. Section II goes over the existing research that has been done in the field and the ones that we would be using to compare later in the article. In Section III, we are comparing the performance of the algorithms developed by authors in the preceding section. In Section IV, we present our analysis on the performance of the models discussed in the previous section. Our suggestions on relative improvement in the models discussed are described extensively in Section V. Finally, we present our conclusion in Section VI.

II. Literature Review

Several methods have been introduced for medical image segmentation specifically for pneumonia. In the study done by Hesamian et al. [3], the authors provide a description of state of the art deep learning techniques utilised for modern day medical image segmentation and the challenges faced in applying those techniques. Different types of CNNs and their applications form the basis and the backbone of this research. They talk about Fully Convolutional Network (FCN) developed by Long et al. [4] where the last fully connected layer is replaced a fully convolutional layer which allows for better performance compared to previous networks. They also talk about 2.5D data approach for the problem which carries richer spatial data as compared to 1D data but is still computationally less expensive compared to 3D information. Lastly, they write about the use of RNNs and LSTMs, a type of RNN, in medical image segmentation. As RNNs are powered by recurrent nodes they have the power to memorise patterns and generalise the context of the image.

But, the study by Hesamian el al. [3] is focused on the medical image segmentation in general. For this review, we have focused on the papers discussed below.

Our first review is based on the paper [5], where Goyal et al. tackled the problem of early detection of viral pneumonia by proposing a novel deep learning framework, which categorises the X-Ray images into various classes namely 'Normal', 'Bacterial Pneumonia', 'Viral Pneumonia', and 'Covid-19'. The model that they have proposed is a features based RNN-LSTM model and is called F-RNN-LSTM which has reduced the training time and has increased the accuracy of classification.

The two datasets that they have used are publicly available datasets from the Kaggle repository and were split using 70-30 train-test split rule. The first dataset is the Covid-19 Radiography dataset (C19RD) which contains a total of 2905 samples and 3 classes – Normal (1341), Viral Pneumonia (1345), and Covid-19 (219). The second one is the Chest X-Ray Images for Pneumonia (CXIP) dataset which contains a total of 5856 samples and 3 classes – Normal (1583), Viral Pneumonia (1483), and Bacterial Pneumonia (2790).

The pipeline that Goyal et al. have followed in [5] starts with first enhancing the quality of the raw images using median filtering technique, then histogram equalisation is done to improve the contrast in the images, and finally adjusting the intensity of the pixels. In the next step, they have used enhanced images for adaptive segmentation to estimate the ROIs and extract parts of the image which are only specific to the lungs. In the third step, they have then identified the Regions of Interest (ROIs) and have extracted the features from those ROIs (HOG features, texture features, Intensity features, and Geometric invariant moment features) and have applied normalisation to scale the features. These features then are used as the input for RNN model which then is used to create an LSTM network. The LSTM network is finally connected to a fully connected neural network, a softmax layer and a final layer that performs classification. The architecture displayed in Fig. 1 is taken from [5] and is an overview of what Goyal et al. have proposed in their research work.

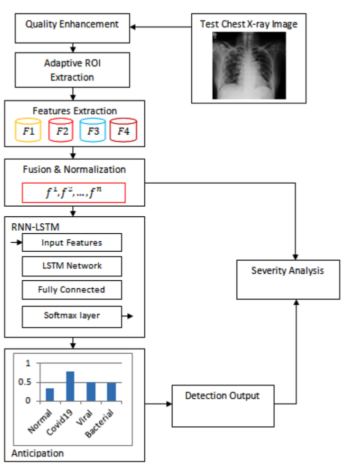

Fig. 1: Proposed F-RNN-LSTM architecture by Goyal et al. in [5]

The second paper that we have reviewed is based on the paper [6], where Elshennawy and Ibrahim have proposed a Deep-Pneumonia Framework for classification and detection of Pneumonia using four models. Out of the four developed models, we have reviewed two proposed models based on CNN and LSTM-CNN deep learning techniques. The architecture discussed in the paper consists of two tiers. First tier focuses on pre-processing the CXR images and carries out tasks like image resizing to a dimension of 224x224x3, image augmentation by flipping/rotating/skewing, image normalisation to [0, 1] interval, and splitting of the dataset. Second tier focuses on extraction of features from the pre-processed image and then performing classification based on four deep learning models. The architecture displayed in Fig. 2 is taken from [6] and is an overview of what Elshennawy and Ibrahim have proposed in their research work.

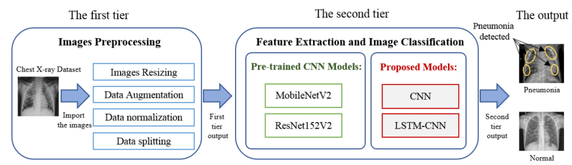

Fig. 2: Proposed Deep-Pneumonia architecture by Elshennawy and Ibrahim in [6]

The dataset that they have used to train their networks on is a publicly available CXIP dataset on Kaggle which contains a total of 5856 samples and 3 classes – Normal (1583), Viral Pneumonia (1483), and Bacterial Pneumonia (2790). They have combined the images in Viral Pneumonia and Bacterial Pneumonia to create one class of images indicating Pneumonia. These images were then augmented and the final dataset contained 30,855 images out of which 8353 images belonged to the Normal class and 22,502 images belonged to the Pneumonia class. They finally split the data into a training set which constituted 70 percent of the data and validation set which contained the remaining 30 percent of the data.

Elshennawy and Ibrahim in [6] have developed four deep learning based models namely CNN, LSTM-CNN, Resenet152V2, and MobilenetV2. For the scope of this review, we are focusing on the first two models. The first CNN based model consisted of an input layer, feature extraction layers, and classification layers. The feature extraction layers were made up of four CNN blocks which consisted of a convolution layer, a batch normalisation layer, and finally a Rectified Linear Unit (ReLU) layer. The CNN architecture also had max pooling layers along with dropout layers. The extracted features were then passed on to a dense, deeply connected neural network in the form of one dimensional array. These features were passed through three dense layers and four dropout layers and the final binary classification was done using sigmoid activation on a dense layer. Fig. 3 describes the proposed CNN architecture in [6].

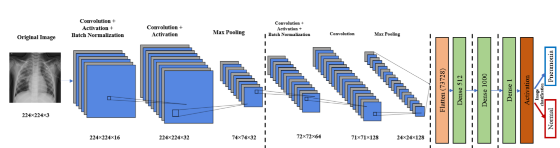

Fig. 3: First model: A CNN-based architecture by Elshennawy and Ibrahim in [6]

The second model discussed in [6] was based on a combination of LSTM-CNN. The first step that was carried out was batch-normalisation to prepare the data for ingestion into the LSTM network. The main aspect was to convert the images into a time series data using the concept of Time Distribution which made the data suitable for LSTM. The architecture that followed the LSTM network was similar to the CNN architecture with minor changes in the fully connected dense layers consisting of two blocks of dense dropout layers and final layer which carried out the binary classification using sigmoid activation on a dense layer. Fig. 4 describes the proposed LSTM-CNN architecture in [6].

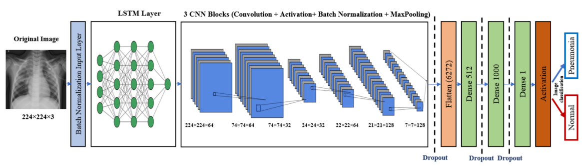

Fig. 4: Second model: An LSTM-CNN based architecture by Elshennawy and Ibrahim in [6]

The next paper that we have reviewed is based on [7], where Rahman et al. discuss four popular deep learning CNN models. These four models are namely: AlexNet, Residual Network (ResNet), Dense Convolutional Network (DenseNet), and SqueezeNet, and are then discussed briefly in the paper. AlexNet is a pre-trained network made up of five convolutional layers which also contain three pooling layers, two fully connected dense layers, and a softmax layer for classification. ResNet is another pre-trained network which contains 18 layers as the name suggests and the idea behind using ResNet was to solve the problem of vanishing gradient and degradation problem. The third network that they have used is DenseNet201 from the family of DenseNets. It is a narrow network and requires less parameters to train than a CNN as a DenseNet does not focus on learning same feature maps again and again. Another property of DenseNet is that the original image is accessible to every layer in the network along with gradients from the loss function and hence it takes less time for convergence. Final pre-trained model that they have used is SqueezeNet. The main characteristic of this network is that the module which sets it apart, called as fire module, is made up of squeeze layer, which has 1x1 convolutional filters and expand layer which has 1x1 and 3x3 convolutional filters. The architecture displayed in Fig. 5 is taken from [7] and is an overview of what Rahman et al have discussed in their work.

The dataset that Rahman et al. have used in [7] is a Kaggle Chest X-Ray Pneumonia dataset. The data contained a total of 5247 CXR images of resolutions varying from 400p to 2000p. There were 3 classes of images - Normal (1341), Viral Pneumonia (1345), and Bacterial Pneumonia (2561). They also performed data augmentation using techniques of image rotation, image translation, and image scaling. The final dataset that they used for training contained 4500 images for each class and close to 200 images for each class for testing.

Next paper that we have reviewed has been proposed by F. Demir in [8] which proposed a new approach based on a deep

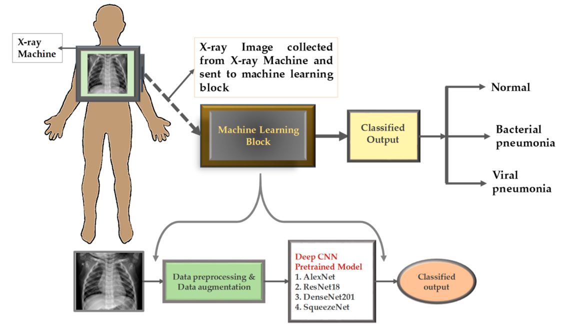

Fig. 5: Overview of the architecture by Rahman et al. in [7]

LSTM architecture named DeepCoroNet to detect Covid-19 and Pneumonia. The architecture had two main components. First component was responsible for pre-processing the CXR images which began with gradient operation using the Sobel, Roberts and Prewitt operation to make spot regions more evident in the images, which in-turn improved the performance of the Marker-Controlled Watershed Segmentation (MCWS). The next step in image pre-processing was spot segmentation using MCWS to reduce the grey tones in the CXR images. The final step in pre-processing was to resize the image to a 100x100 according to the input layer of the Deep-LSTM network. The second component was Deep-LSTM network which was made up of a sequence data creating block which created a one dimensional vector from the pre-processed images followed by an LSTM network which constituted five layers including the LSTM layer, a fully connected layer, a ReLU layer, a dropout layer and finally softmax layer which performed the final classification. The architecture displayed in Fig. 6 is taken from [8] and is an overview of what Demir has discussed in the research work.

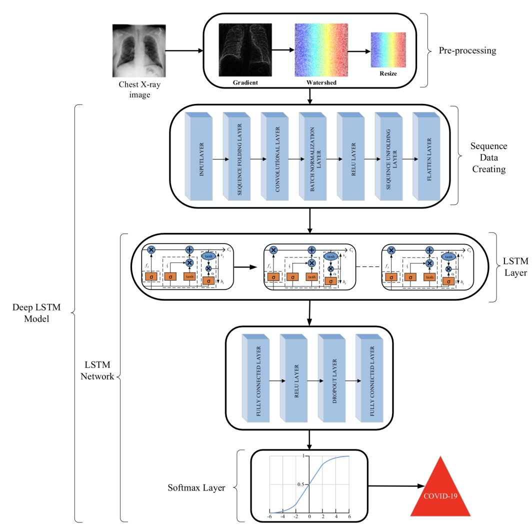

Fig. 6: Overview of the architecture proposed by Demir in [8]

The dataset that Demir has used in [8] is a public dataset compiled from various sources (the COVID-19 and normal images were obtained from Kaggle, while the pneumonia samples were added from a dataset by Wang et al. in [9]), containing a total of 1061 CXR images and the data labels were created by specialists and radiologists and were classified into three categories - Normal (200 images), Pneumonia (500 images), and Covid-19 (361 images). Demir then split the data into training and testing using three splits of 80-20, 70-30, and 60-40. The model was then trained and tested on raw and MCWS images based on these three splits.

The final research paper that we have reviewed has been proposed by Erdem and Aydin in [10] which proposed a novel CNN based model to detect Pneumonia. The proposed network consisted of 3 blocks of 6 convolutional layers and 3 blocks of 6 separable convolutional layers and all these blocks used 3x3 filters. Every block was then separated by max pooling layer containing a 2x2 filter. The first three blocks used 16, 32, and 64 filters, respectively and the next 3 blocks with separable convolutional layers used 32, 64, and 128 filters, respectively. For hidden layers, ReLU activation function is used for the activation process. The model also tried to deal with overfitting by using dropout layers. The model used 5 dropout layers, all of which had different dropout rates of 25, 20, 90, 70, and 50 percent, respectively. The final part of the network contained four fully connected, flattened layers with the last layer being the sigmoid activation layer for classification. The architecture displayed in Fig. 7 is taken from [10] and is an overview of what Erdem and Aydin have discussed in their research work.

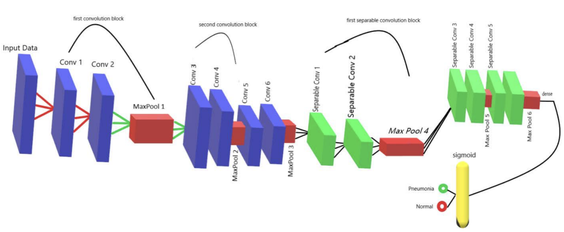

Fig. 7: Overview of the architecture proposed by Erdem and Aydin in [10]

The dataset that Erdem and Aydin have used in [10] was taken from Guangzhou Women and Children's Medical Center and was open to use. It was then split into training, validation, and testing set. Before beginning training, the images were reshaped to 150x150x3 dimensions

III. Comparison of Papers

In this section, we are comparing the results of the deep learning models that were trained in the research papers that we have reviewed. The chosen performance criteria for comparison are Accuracy, F1-score, and Area Under Curve (AUC) score. Accuracy is defined as the fraction of predictions that the learning model got right. F1 score is defined as the harmonic mean of precision and recall of the model. AUC score is the measure of the capability of the model in distinguishing between the classes that it is predicting.

Before comparing, it should be understood that not all of the models are trained on exact same data. Some of the models have used data augmentation before training, while some have used a different dataset without augmentation. Moreover, not all research papers have used the same evaluation metrics as well. Hence, we cannot be certain when saying that one proposed model is superior to other models. For those reasons, the comparison that has been done in this review paper is to highlight performance of various models proposed by researchers in the field of Medical Image Segmentation using Deep Learning techniques and build a comparison to some extent. The performance comparison is given in the Table 1.

Goyal et al. in [5] proposed a F-RNN-LSTM architecture which achieved the best accuracy score of 95.04 percent and best F1 score of 95.19 amongst the three models that they trained on different pre-processed data. They did not compute AUC score in their research.

Elshennawy and Ibrahim in [6] proposed a Deep-Pneumonia framework with four models and out of those, two were based on CNN and LSTM-CNN. The CNN based model achieved an accuracy of 92.19 percent, F1 score of 93.79, and AUC score of 96.92 whereas the LSTM-CNN model achieved an accuracy of 91.8, F1 score of 92.29, and AUC score of 95.49.

Rahman et al. in [7] compared four models - AlexNet, ResNet, DenseNet, and SqueezeNet. They tested these models for three sets of classes - Normal/Pneumonia, Normal/Bacterial Pneumonia/Viral Pneumonia, and Bacterial Pneumonia/Viral Pneumonia. The best accuracy that they achieved was 98 percent when DenseNet201 was trained to distinguish between Normal and Pneumonia. Also, they achieved the best F1 score of 98.1 and best AUC score of 98 on the DenseNet201 model as well.

Demir in [8] proposed DeepCoroNet framework and tested the model on three different splits of the data: 80-20 split, 70-30 split, and 60-40 split. The dataset that was curated for this research work was very as compared to other research papers. The highest accuracy that was achieved was 100 and highest F1 score was also 100 for 80-20 split.

Erdem and Aydin in [10] proposed a CNN based network and tested the model on Guangzhou Women and Children's Medical Center. The model achieved an accuracy of 88.62 percent and an F1 score of 91.45.

IV. Understanding and Analysis

After carefully perusing through various research papers, there are various points that we would like to point out and that we understood from the reading. Our understanding and analysis is presented below:

A. *Wide use of combinations of various deep learning models*

From our readings, we can see that most of the researchers now focus on harnessing the power of deep learning models like CNN, RNN, and LSTM in a framework that utilises the best bits of combinations of models instead of just focusing on one deep learning model. Elshennawy and Ibrahim in [6] used a combination of LSTM-CNN and achieved good accuracy and F1 score. This seems intuitive because a single model can lack certain aspects of learning and that can be avoided by using various deep learning models together.

Research Paper	Classifier	Data	Accuracy	F1	AUC
Goyal et al. [5]	F-RNN-LSTM	Raw features	89.36	90.22	-
Goyal et al. [5]	F-RNN-LSTM	Min-Max-Normalised	93.55	94.00	-
Goyal et al. [5]	F-RNN-LSTM	Robust Normalisation	95.04	95.19	-
Elshennawy et al. [6]	CNN	5856 images (1583 normal, 4273 pneumonia)	92.19	93.79	96.92
Elshennawy et al. [6]	LSTM-CNN	5856 images (1583 normal, 4273 pneumonia)	91.80	92.29	95.49
Rahman et al. [7]	AlexNet	Normal and Pneumonia	94.5	94.3	94.2
Rahman et al. [7]	ResNet18	Normal and Pneumonia	96.4	96.5	96.3
Rahman et al. [7]	DenseNet201	Normal and Pneumonia	98.0	98.1	98.0
Rahman et al. [7]	SqueezNet	Normal and Pneumonia	96.1	96.1	96.0
Rahman et al. [7]	AlexNet	Normal, Bacterical Pneumonia and Viral Pneumonia	88.4	88.5	91.1
Rahman et al. [7]	ResNet18	Normal, Bacterical Pneumonia and Viral Pneumonia	87.7	90.9	91.0
Rahman et al. [7]	DenseNet201	Normal, Bacterical Pneumonia and Viral Pneumonia	93.3	93.5	95.0
Rahman et al. [7]	SqueezNet	Normal, Bacterical Pneumonia and Viral Pneumonia	86.1	86.5	89.5
Rahman et al. [7]	AlexNet	Bacterial and Viral Pneumonia	90.0	92.1	89.0
Rahman et al. [7]	ResNet18	Bacterial and Viral Pneumonia	87.0	87.3	87.0
Rahman et al. [7]	DenseNet201	Bacterial and Viral Pneumonia	95.0	95.2	95.2
Rahman et al. [7]	SqueezNet	Bacterial and Viral Pneumonia	83.0	84.0	83.0
Demir [8]	DeepCoroNet	Normal (200), Pneumonia (500), Covid-19 (361) with 80-20 split	100	100	-
Demir [8]	DeepCoroNet	Normal (200), Pneumonia (500), Covid-19 (361) with 70-30 split	100	99	-
Demir [8]	DeepCoroNet	Normal (200), Pneumonia (500), Covid-19 (361) with 60-40 split	100	100	-
Erdem et al. [10]	CNN	Normal (1583) and Pneumonia (4273)	88.62	91.45	-

Table 1. Comparison of Performance of the models proposed in the reviewed research papers

B. Limited Annotated Data

Deep Learning facilitates segmentation accuracy by learning complex hypotheses. It does it by training on substantial number of annotated data and collecting large annotated medical image data is tedious and time-consuming. Various issues like data privacy and anonymisation of data need to be addressed before data collection process starts. Moreover, from the readings, we can see that we have a shortage of proper data for training extensively large Deep Learning models. Most of the models that we looked at were trained on around 5000 images, which is a very less amount of data. Additionally, for image segmentation and particularly medical image segmentation, it is very difficult to gather high quality data. Hence, it is important to pre-process the data to enhance the image quality. In our readings, we have seen that techniques like histogram equalisation, median filtering,

Another important task is to deal with limited annotated data is to augment it by various image processing techniques. In our readings, we have seen techniques implemented like flipping the image, mirror the image, rotating the image, image scaling, and changing the grey values. Another method is to break down the image into patches that overlap with the parent image.

C. Class Imbalance

Generally, in medical image processing samples for diseased individuals are comparatively less that the labelled images for normal individuals. In our readings, we can see that there were a lot of images related to Pneumonia whereas there were very few related to Normal condition or even Covid-19 condition. This can be resolved by trading off the number of normal samples or applying aforementioned image pre-processing techniques.

D. Vanishing Gradient Problem

Deep neural networks often deal with the issue of vanishing gradient problem as discussed in [6], i.e., the final loss cannot be propagated as it vanishes in hidden layers. Solution to this issue is to up-scale the loss using deconvolution and pass it to the SoftMax layer.

E. Transfer Learning

We have witnessed that transfer learning can help computer vision tasks. A pre-trained model like BERT, AlexNet could be used for predictions by fine tuning the parameters on CXR data. We reviewed that Rahman et al. in [7] used AlexNet, ResNet, DenseNet201, and SqueezNet to great effect and produced great results on a very limited dataset as well.

V. SUGGESTIONS

After reading various research papers and understanding the problems, there are some suggestions that can be implemented to solve problems and limitations faced by the implementations. Some of these are listed below in brief.

1. Bidirectional RNN/LSTM are a great way to handle vanishing gradient problem that can occur in traditional RNNs. By combining the virtues of LSTMs and benefits of bidirectional RNNs, the segmentation of medical data could be performed much better.

2. Encoder-decoder network: These networks use an encoder to reduce the spatial information of the input image to increase the computational performance and then scale up the dimensions again by a decoder.

3. U-Net: Like encoder-decoder network, U-net uses a combination of down sampling and up sampling layer for handling imbalance in the dataset. This is another option to deal with dataset which suffers from class imbalance.

4. Another way of improving accuracy of a model is to combine prediction of multiple models based on a criteria like average or weighted average which can lead to improved results in medical image segmentation. This process is called as Ensemble Learning. It can be explored in future works to see how it performs on CXR images.

VI. Conclusion

This review study presents some of the state-of-the-art deep learning models developed by researchers and their comparative analysis. It was found that in modern day image segmentation, models that are a combination of CNN, RNN, and LSTM are used in tandem rather than a single unit as they each tend to complement each other with different functions for image segmentation. This study has enabled us to understand the problems faced while developing a deep learning framework for medical image segmentation to detect Pneumonia or Covid-19. The biggest problem is to gather high quality CXR image dataset to train complex deep learning models. CXR images tend to be of low clarity and hence it becomes imperative to enhance the quality of the dataset available. Moreover, the amount of data available is also very less for an image segmentation problem and therefore it becomes important to augment the limited amount of data that is available using various techniques like rotation, scaling, mirroring, etc.

After reviewing the papers, we could conclude that deep learning models like CNN, LSTM, and RNN when used together, produce better results than frameworks based on a single deep learning model alone. Also, deep learning models when combined with pre-trained models like AlexNet, ResNet produce even better results.

It can be said that medical image segmentation is a challenging task mainly because of the limited amount of data that is available, but with powerful deep learning techniques, it is possible to achieve the goal in detecting whether a patient has Pneumonia or Covid-19 or not. The problem would become easier if high quality CXR image dataset is curated and then made available to solve an important problem in the medical domain.

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