VISVESVARAYA TECHNOLOGICAL UNIVERSITY

Jnana Sangama, Belagavi – 590018

A TECHNICAL SEMINAR REPORT

ON

"Deep Learning Enables Accurate Diagnosis of Novel Coronavirus(COVID – 19) with CT images"

A Dissertation Submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF ENGINEERING

In

COMPUTER SCIENCE & ENGINEERING

Submitted by

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2020 – 2021

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CERTIFICATE

This is to certify that the Seminar Report titled **"Generative Adversarial Networks"** is a bona fide work carried out by **Mr. Prajwal B Mani (1RG17CS037)** in partial fulfillment for the award of **Bachelor of Engineering** in **Computer Science and Engineering** under **Visvesvaraya Technological University, Belagavi**, during the year **2020-2021.** It is certified that all corrections/suggestions given for Internal Assessment have been incorporated in the report. This technical seminar report has been approved as it satisfies the academic requirements in respect of technical seminar (17CSS86) work prescribed for the said degree.

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DECLARATION

I hereby declare that the technical seminar report entitled **"Deep Learning Enables Accurate Diagnosis of Novel Coronavirus (COVID – 19) with CT images"** submitted to the **Visvesvaraya Technological University, Belagavi** during the academic year **2020-2021**, is record of an original work done by me under the guidance of **Mrs. Pushplata Dubey,** Asst Professor, Department of Computer Science and Engineering, RGIT, Bengaluru in the partial fulfillment of requirements for the award of the degree of **Bachelor of Engineering** in **Computer Science & Engineering.** The results embodied in this technical seminar report have not been submitted to any other University or Institute for award of any degree or diploma.

PRAJWAL B MANI (1RG17CS037)

ACKNOWLEDGEMENT

I take this opportunity to thank my college **Rajiv Gandhi Institute of Technology, Bengaluru** for providing me with an opportunity to carry out this seminar work.

I extend my sincere regards and thanks to **Dr. D G Anand**, Principal, RGIT, Bengaluru and to **Mrs. Arudra A**, Associate Professor and Head, Department of Computer Science and Engineering, RGIT, Bengaluru, for being a pillar of support and encouraging me in the face of all adversities.

I would like to acknowledge the thorough guidance and support extended towards us by **Mrs. Pushplata Dubey**, Assistant Professor, Dept of CSE, RGIT, Bengaluru. Their incessant encouragement and valuable technical support have been of immense help. Their guidance gave me the environment to enhance my knowledge and skills and to reach the pinnacle with sheer determination, dedication and hard work.

I also want to extend my thanks to the entire faculty and support staff of the Department of Computer Science and Engineering, RGIT, Bengaluru, who have encouraged me throughout the course of the Bachelor's Degree.

I want to thank my family for always being there with full support and for providing me with a safe haven to conduct and complete my technical seminar. I will ever grateful to them for helping me in these stressful times.

Lastly, I want to acknowledge all the helpful insights given to me by all my friends during the course of this technical seminar.

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ABSTRACT

A novel coronavirus (COVID – 19) recently emerged as an acute respiratory syndrome, and has caused a pneumonia outbreak world - wide. As the COVID – 19 continues to spread rapidly across the world, Computed Tomography (CT) has become essentially important for fast diagnosis. Thus, it is urgent to develop an accurate computer-aided method to assist clinicians to identify COVID-19-infected patients by CT images. Here, they have collected chest CT scans of 88 patients diagnosed with COVID – 19 from hospitals of two provinces in China, 100 patients infected with bacterial pneumonia, and 86 healthy persons for comparison and modeling. Based on the data, a deep learning-based CT diagnosis system was developed to identify patients with COVID – 19. The experimental results showed that the model could accurately discriminate the COVID – 19 patients from the bacterial pneumonia patients with an AUC of 0.95, recall (sensitivity) of 0.96, and precision of 0.79. When integrating three types of CT images, the model achieved a recall of 0.93 with precision of 0.86 for discriminating COVID – 19 patients from others. Moreover, our model could extract main lesion features, especially the Ground - Glass Opacity (GGO), which are visually helpful for assisted diagnosis by doctors. An online server is available for online diagnosis with CT images by our server (http://biomed.nscc-gz.cn).

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INTRODUCTION

CHAPTER 1

INTRODUCTION

Deep Learning is at the cutting edge of what machines can do, and developers and business leaders absolutely need to understand what it is and how it works. This unique type of algorithm has far surpassed any previous benchmarks for classification of images, text, and voice. It also powers some of the most interesting applications in the world, like autonomous vehicles and real-time translation. There was certainly a bunch of excitement around Google's Deep Learning based AlphaGo beating the best Go player in the world, but the business applications for this technology are more immediate and potentially more impactful.

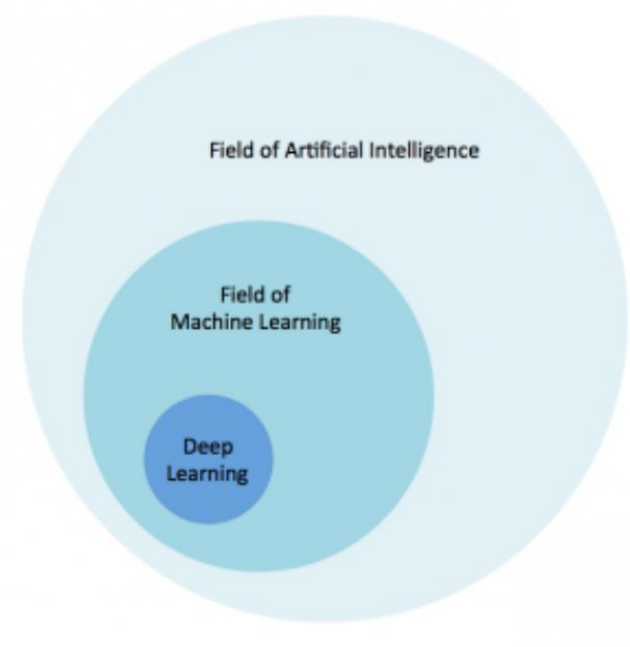


Figure 1(a): Distribution of Domains

Deep learning is a specific subset of Machine Learning, which is a specific subset of Artificial Intelligence. For individual definitions:

- Artificial Intelligence is the broad mandate of creating machines that can think intelligently
- Machine Learning is one way of doing that, by using algorithms to glean insights from data (see our gentle introduction here)
- Deep Learning is one way of doing that, using a specific algorithm called a Neural Network

Neural networks are inspired by the structure of the cerebral cortex. At the basic level is the perceptron, the mathematical representation of a biological neuron. Like in the cerebral cortex, there can be several layers of interconnected perceptrons.

Input values, or in other words our underlying data, get passed through this "network" of hidden layers until they eventually converge to the output layer. The output layer is our prediction: it might be one node if the model just outputs a number, or a few nodes if it's a multiclass classification problem.

The hidden layers of a Neural Net perform modifications on the data to eventually feel out what its relationship with the target variable is. Each node has a weight, and it multiplies its input value by that weight. Do that over a few different layers, and the Net is able to essentially manipulate the data into something meaningful. To figure out what these small weights should be, we typically use an algorithm called Backpropagation.

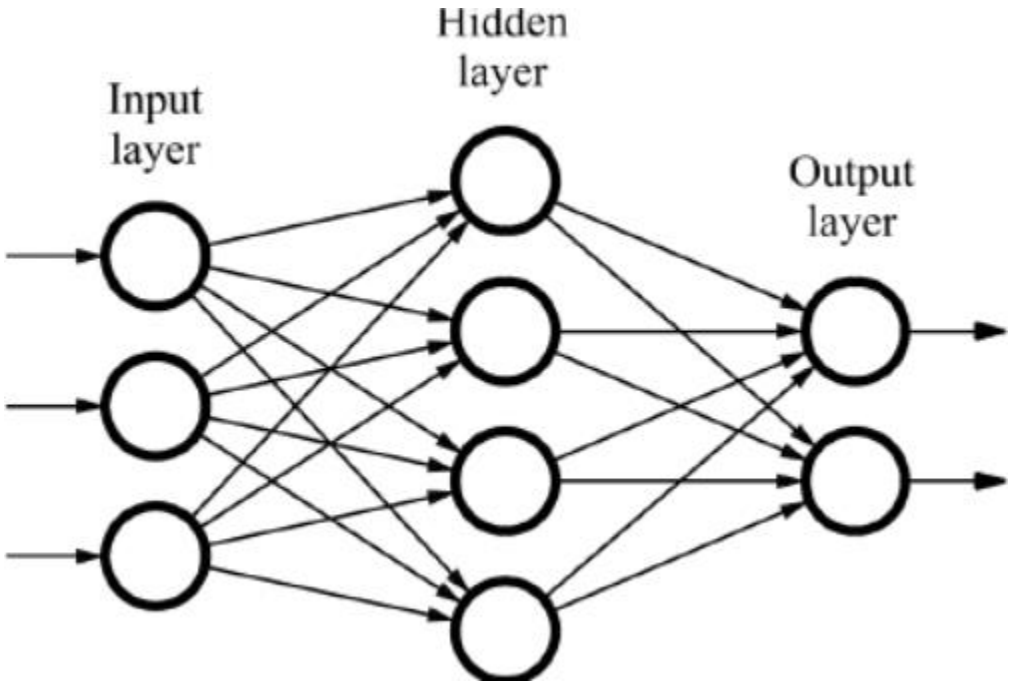


Figure 1(b): Simple Neural Network Structure

Now coming to our technical seminar main topic is Covid-19, In late December 2019, a cluster of pneumonia cases with unknown etiology was reported in Wuhan city, Hubei Province, China.1 Deep sequencing analyses from lower respiratory tract samples revealed a novel coronavirus that was currently named 2019 novel coronavirus (COVID – 19) by the World Health Organization (WHO), which resembled severe acute respiratory syndrome coronavirus (SARS – CoV).3 Outbreaks in healthcare workers and families indicated human-to-human transmission. The COVID – 19 is a beta – CoV of group 2B with at least 70%

similarity in genetic sequence to SARS – CoV and is the seventh member of the family of enveloped RNA coronavirus that infects humans.

Since January 17, the confirmed cases dramatically increased, and COVID – 19 has been designated as a public health emergency of international concerns by the WHO. Currently as of May 2021 a total of 16.7Cr confirmed cases and and 34.8L deaths around the world. The COVID – 19 has posed significant threats to international health.

The spectrum of this disease in humans is yet to be fully determined. Signs of infection are nonspecific, including respiratory symptoms, fever, cough, dyspnea, and viral pneumonia.With the daily increase in the number of newly diagnosed and suspected cases, the diagnosis has become a growing problem in major hospitals due to the insufficient supply of nucleic acid detection boxes and limited detection rates in the epidemic area. Computed tomography (CT) and radiography have thus emerged as integral players in the COVID – 19's preliminary identification and diagnosis. Computed tomography (CT) and radiography have thus emerged as integral players in the COVID – 19's preliminary identification and diagnosis. In this study, we have developed a deep learning-based lung CT diagnosis system to detect the patients with COVID – 19, which can automatically extract radiographic features of the novel pneumonia, especially the ground-glass opacity (GGO) from radiographs.

MATERIALS AND METHODS

CHAPTER 2

MATERIALS AND METHODS

2.1 Data Acquisition

This study is based on the reliable resources that were provided by the Renmin Hospital of Wuhan University, and two affiliated hospitals (the Third Affiliated Hospital and Sun Yat-Sen Memorial Hospital) of the Sun Yat-sen University in Guangzhou.

We obtained totally CT images of 88 COVID-19 infected patients, which comprised of 76 and 12 patients from the Renmin Hospital of Wuhan University and the Third Affiliated Hospital, respectively. Wuhan's chest CT examinations were performed with a 64-section scanner (Optima 680, GE Medical Systems, Milwaukee, WI, USA) without the use of contrast material. The CT protocol was as follows: 120 kV; automatic tube current; detector, 35 mm; rotation time, 0.35 second; section thickness, 5 mm; collimation, 0.75 mm; pitch, 1-1.2; matrix, 512×512; and inspiration breath hold. The images were photographed at lung (window width, 1000–1500 HU; window level, –700 HU) and mediastinal (window width, 350 HU; window level, 35– 40 HU) settings. The reconstructions were made at 0.625 mm slice thickness on lung settings. These data consist of only transverse plane images of lung. For patients in Guangzhou, we obtained his/her lung images in anterior view, lateral view and transverse view. The chest CT examinations were performed with a 64-slice spiral scanner (Somatom Sensation 64; Siemens, Germany). All patients' nasopharyngeal swabs were subjected to nucleic acid kit lysis extraction and calculation to the laboratory of Renmin Hospital of Wuhan University performed fluorescence RT-PCR to detect the viral nucleic acid gene sequence, and compared it with the novel coronavirus nucleocapsid protein gene (nCoV-NP) and the novel coronavirus open reading coding frame lab (nCoV ORFlab) sequence. The results were positive, and the HRCT image quality of the chest was acceptable, with no significant artifacts or missing images. For comparison, we also retrieved CT underwent chest images of 86 healthy people and 100 patients with bacterial pneumonia from the Renmin Hospital of Wuhan University and Sun Yat-Sen Memorial Hospital.

2.2 Model Architecture and Model Training

They developed a deep learning – based CT diagnosis system (referred to as DeepPneumonia) to assist doctors to detect the COVID-19 causing pneumonia and to localize

the main lesions. As shown in figure, our fully automated lung CT diagnosis system was developed by three main steps. First, we extracted the main regions of lungs and filled the blank of lung segmentation with the lung itself to avoid noises caused by different lung contours. Then, we designed a Details Relation Extraction neural network (DRE-Net) to extract the top – K details in the CT images and obtain the image-level predictions. Finally, the image-level predictions were aggregated to achieve patient level diagnosis.

2.3 Data preprocessing

Each set of 3D CT images was equally divided into 15 slices. The slices with incomplete lung were removed. The lung region in each slice were automatically extracted by the open source package OpenCV. As the lung contours are of large differences between humans, the images were filled with an background composed of 10 translational and rotational lungs. Finally, we kept 88 COVID-19 patients with 777 CT images, 100 bacterial pneumonia patients with 505 slices, and 86 healthy people with 708 slices in this study.

2.4 Architecture of ResNet – 50

The architecture of ResNet50 has **4 stages** as shown in the diagram below**.** The network can take the input image having height, width as multiples of 32 and 3 as channel width. For the sake of explanation, we will consider the input size as 224 x 224 x 3. Every ResNet architecture performs the initial convolution and max-pooling using 7×7 and 3×3 kernel sizes respectively. Afterward, Stage 1 of the network starts and it has 3 Residual blocks containing 3 layers each. The size of kernels used to perform the convolution operation in all 3 layers of the block of stage 1 are 64, 64 and 128 respectively. The curved arrows refer to the identity connection. The dashed connected arrow represents that the convolution operation in the Residual Block is performed with stride 2, hence, the size of input will be reduced to half in terms of height and width but the channel width will be doubled. As we progress from one stage to another, the channel width is doubled and the size of the input is reduced to half.

For deeper networks like ResNet50, ResNet152, etc, bottleneck design is used. For each residual function ***F,*** 3 layers are stacked one over the other. The three layers are **1×1, 3×3, 1×1** convolutions. The **1×1** convolution layers are responsible for reducing and then restoring the dimensions. The **3×3** layer is left as a bottleneck with smaller input/output dimensions.

Finally, the network has an Average Pooling layer followed by a fully connected layer having 1000 neurons (ImageNet class output).

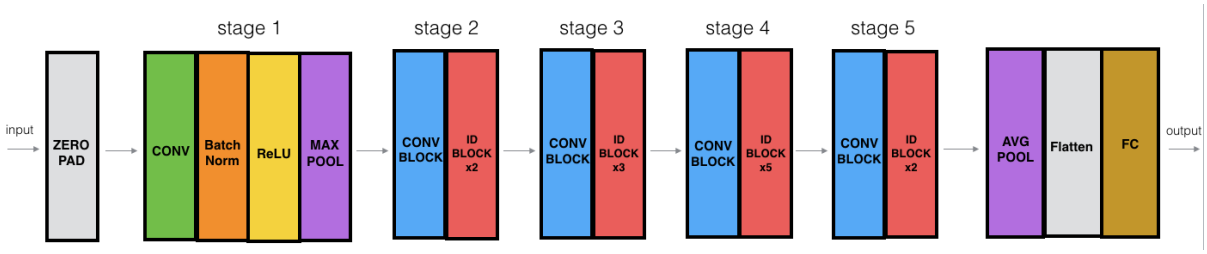


Figure 2.4(a): ResNet 50 Architecture

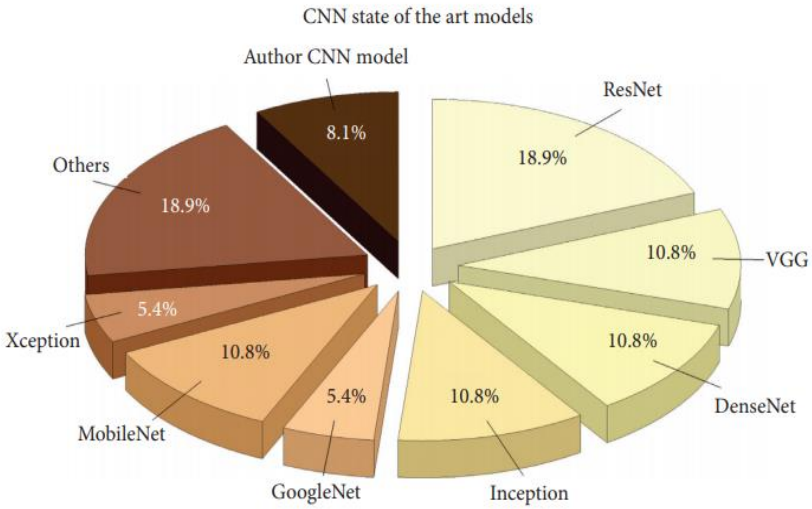


Figure 2.4(b): Distribution of different CNN Models for Covid data

2.5 DRE – Net

Our training models were concretely constructed on the pretrained ResNet – 50, on which the Feature Pyramid Network (FPN) was added to extract the top – K details from each image. An attention module is coupled to learn the importance of each detail. By using the FPN and attention modules, our model can not only detect the most important part of images, but also interpret the outputs by the neural network.

2.6 Aggregation

The image-level scored results of slices were aggregated for each patient. Here, the mean pooling was used to integrate the image-level results into the morbidity of each person as the human-level result.

2.7 Implementation and Evaluation

For practical purposes, we designed the models with two tasks, discriminating COVID – 19 infected patients from the bacterial-infected patients, and separating COVID – 19 patients from healthy controls, respectively. For each task, we employed the patient-level split strategy following the LUNA16 competition by using random splits of 60%/10%/30% for training, validation, and test sets, respectively. The training set were used to train models, and the validation set was used to optimize the hyperparameters for the best performance. The final optimal models were independently assessed on the test set.

We computed accuracy, precision, recall as

$$\text{Accuracy} = \text{TP} + \text{TN} / \text{TP} + \text{FP} + \text{TN} + \text{FN}$$

$$\text{Precision} = \text{TP} / \text{TP} + \text{FP}$$

$$\text{Recall} = \text{TP} / \text{TP} + \text{FN}$$

where TP, TN, FP, and FN are the numbers of true positives, true negatives, false positives, and false negatives, respectively. We also computed Area Under the receiver-operating characteristics Curve (AUC) by the scikit-learn 0.19.

RESULTS AND DISCUSSIONS

CHAPTER 3

RESULTS AND DISCUSSIONS

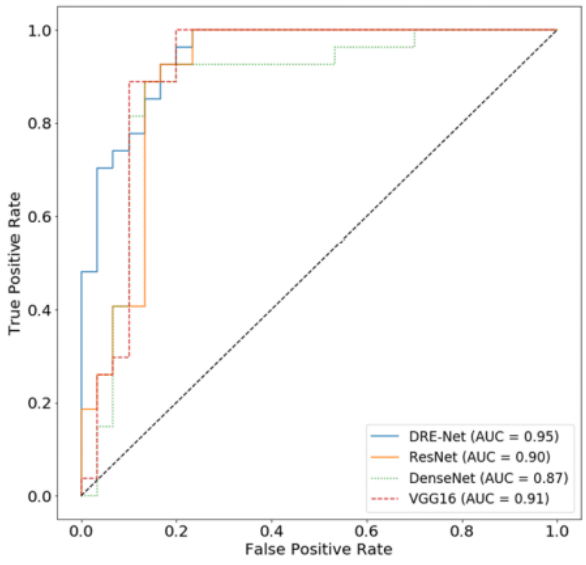
3.1 Deep Learning Model for Pneumonia Classification

An important tool for assisted diagnosis is to accurately discriminate between bacterial pneumonia and viral pneumonia (COVID – 19) in order to decrease the unnecessary waste of medical resources. To this end, we built a pneumonia classification model based on 88 COVID – 19 and 100 bacterial pneumonia patients, from which we collected 777 and 505 images. By tuning hyperparameters according to the validation set, we achieved AUC of 0.91 in the image level, and AUC of 0.95 in the human level. The performances are essentially the same on the test set with AUC of 0.92 in the image level, and AUC of 0.95 and recall of 0.96 in the human level. The higher AUC in the test set is partly due to the relatively small datasets. To indicate the effectiveness of our proposed DRENet architecture, we also employed deep residual network (Resnet), 13 DenseNet17 , and VGG1618 for comparisons. As shown in Table 1, by selecting the topK important details and the relationships among them, our DRE – Net improves about 7.0% recall and 3.0% F1 – score over VGG16 with the same fold assignments, respectively. Figure shows the receiver-operating characteristic curves for comparisons with other baseline models and the confusion matrix of DRE-Net on the test set.

Additionally, we also performed experiments on 88 COVID – 19 patients and 86 healthy persons, from which 777 and 708 images were collected. By tuning hyperparameters on the 10% validation set, we achieved AUC of 0.97 in the image level, and 0.99 in the patient level. The performances are essentially the same on the test set with 0.98 in the image level, and AUC of 0.99 and recall of 0.93 in the patient level.

Model	AUC	Recall	Precision	F1-score	Accuracy
VGG16	0.91	0.89	0.80	0.84	0.84
DenseNet	0.87	0.93	0.76	0.83	0.82
ResNet	0.90	0.93	**0.81**	0.86	0.86
DRE-Net	**0.95**	**0.96**	0.79	**0.87**	**0.86**

Table 3.1: Results of various models for Pneumonia Classification



A

Test set= 57	Predicted: NO	Predicted: YES
Actual: NO	TN = 23	FP = 7
Actual: Yes	FN = 1	TP = 26

B

Figure 3.1: Confusion matrix and performance chart Pneumonia Classification

3.2 Deep Learning Model for Pneumonia Diagnosis

Additionally, we also performed experiments on 88 COVID-19 patients and 86 healthy persons, from which 777 and 708 images were collected. By tuning hyperparameters on the 10% validation set, we achieved AUC of 0.97 in the image level, and 0.99 in the patient level. The performances are essentially the same on the test set with 0.98 in the image level, and AUC of 0.99 and recall of 0.93 in the patient level.

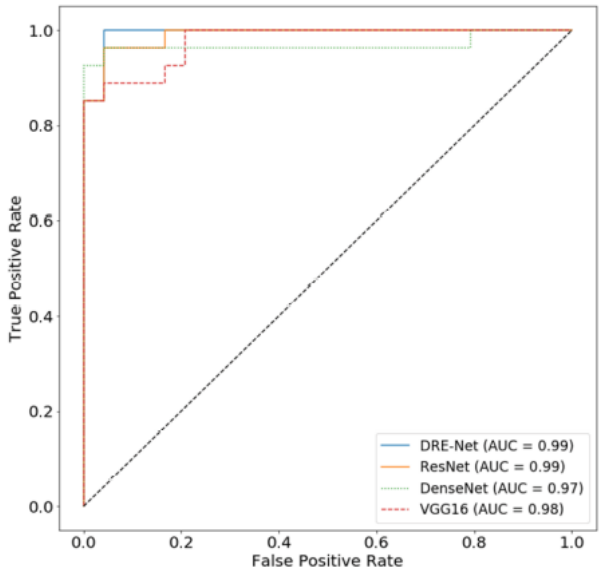
As shown in the below Table 3.2, DRE – Net achieved better performance than those of ResNet, DenseNet and VGG16 because of the strong power of details extraction. The high performance of these deep learning models also demonstrated that the CT images of pneumonia patients and healthy people were well differentiated.

Another advantage of DRENet is its ability to detect potential lesion regions for interpretation. For visualization, we selected two successfully predicted pneumonia patients from the test set, and showed three slice images with the highest scores for each patient. The detected regions by DRENet contained ground-glass opacity (GGO) abnormality, which has been reported as the most important character for COVID-19 patients by recent studies To quantify the potential lesion regions, we also drew the heat maps through the Gradient – weighted Class Activation Mapping (Grad – CAM) The visualizations by Grad – CAM were essentially consistent to detect potential lesion regions while providing more information.

These findings indicate that DRENet could detect key features. The detected features provide reasonable clues for the judgements, which are especially helpful for diagnoses by doctors.

Model	AUC	Recall	Precision	F1-score	Accuracy
VGG16	0.98	0.89	0.92	0.91	0.90
DenseNet	0.97	0.92	0.85	0.92	0.92
ResNet	0.99	0.89	0.96	0.92	0.92
DRE-Net	**0.99**	**0.93**	**0.96**	**0.94**	**0.94**

Table 3.2: Results of various models for Pneumonia Diagnosis



Test set= 51	Predicted: NO	Predicted: YES
Actual: NO	TN = 23	FP = 1
Actual: Yes	FN = 2	TP = 25

A B

Figure 3.2(a): Confusion matrix and performance chart Pneumonia Diagnosis

In order for real-world assisted diagnosis in hospitals, we further performed three-class classification experiments by adding pneumonia patients caused by bacteria. To this end, we built a model by the proposed DRENet learning architecture based on 88 COVID-19, 100 bacterial pneumonia patients, and 86 healthy persons, consisting of 777, 505 and 708 CT images, respectively. As shown in Table 3.2, DRENet achieved a precision of 0.93 with a recall of 0.93 in average, corresponding to F1 – score of 0.93 as well. By comparison, the F1 – score of DRENet is 2% higher than the next best ResNet and VGG16. DenseNet performed the worst

with F1-score of 0.88. Fig. 3.2 shows the confusion matrix of the DRENet on the pneumonia three-class classification. We observed that the model can discriminate all healthy persons from pneumonia patients while make only six wrong predictions in classifying the bacterial pneumonia and viral pneumonia (COVID-19). When considering the separation of COVID-19 patients from others, the model achieved a recall of 0.93 and precision of 0.86

By examining two COVID-19 patients who were wrongly predicted to be caused by bacteria, we found their respective predicted scores were 0.46 and 0.39 in the patient level. These scores were both marginally lower than the threshold of 0.5. As shown in figure, although the patient C has a score of 0.46 in the patient level, three most suspected slice images (the highest scores in the image level) all have scores greater than 0.5 in the image level. Therefore, DRENet could still assist doctors to make correct decisions by visualizing key images in occasionally wrong cases. On the other hand, the patient D of bacterial pneumonia was wrongly predicted as the COVID – 19 patient. The misjudgements might be caused by the GGO abnormalities appearing in the patient of bacterial pneumonia for unknown reasons, as shown in the rectangles.

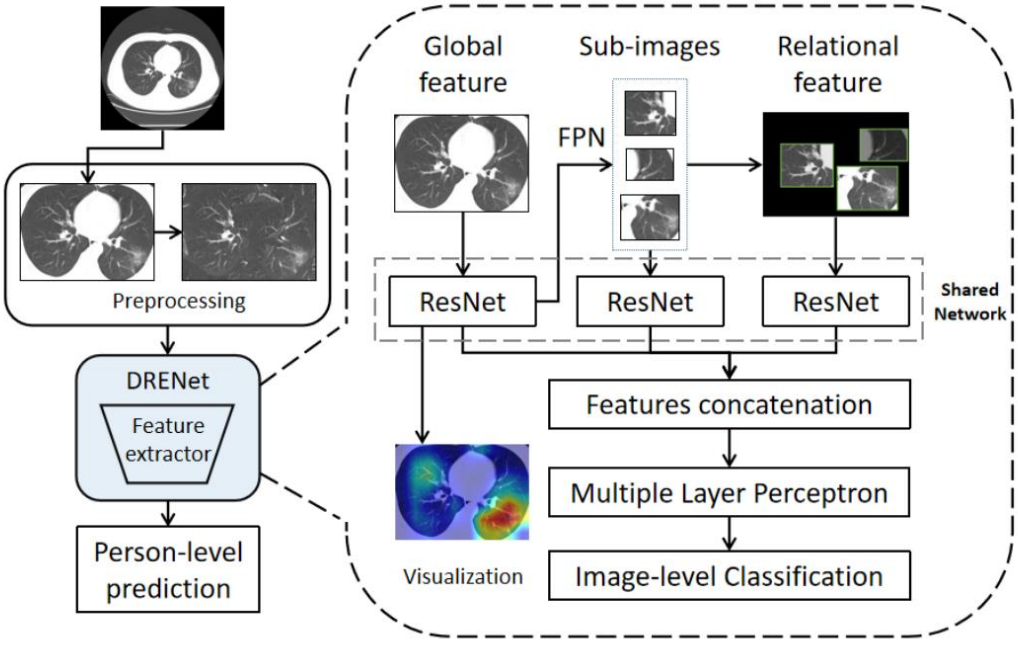


Figure 3.2(b): Proposed Architecture of DRENet

MODEL INTERPRETATION AND VISUALIZATION

CHAPTER 4

MODEL INTERPRETATION AND VISUALIZATION

Another advantage of our model is its interpretability. In diagnosis of COVID – 19, Ground – Glass Opacity (GGO) in CT image is one of the most important factors to recognize the patients.Therefore, we expected our model can localize GGO in CT images, especially in the early stage patients and suspected patients. We visualized the automatically extracted details of two successfully predicted pneumonia patients from the test set. For each patient, the top 3 predicted slices and the extracted details were indicated with predicted scores above 0.8 (range from 0 to 1). As shown in the Figure below , the assessments of DRNet mainly focused on the region of the GGO abnormality. These findings indicate that DRNet learned to assess the correct features instead of learning image correlations. Moreover, our model provides reasonable clues on the factors for its judgements, which is of great help to assist doctors in diagnosis.

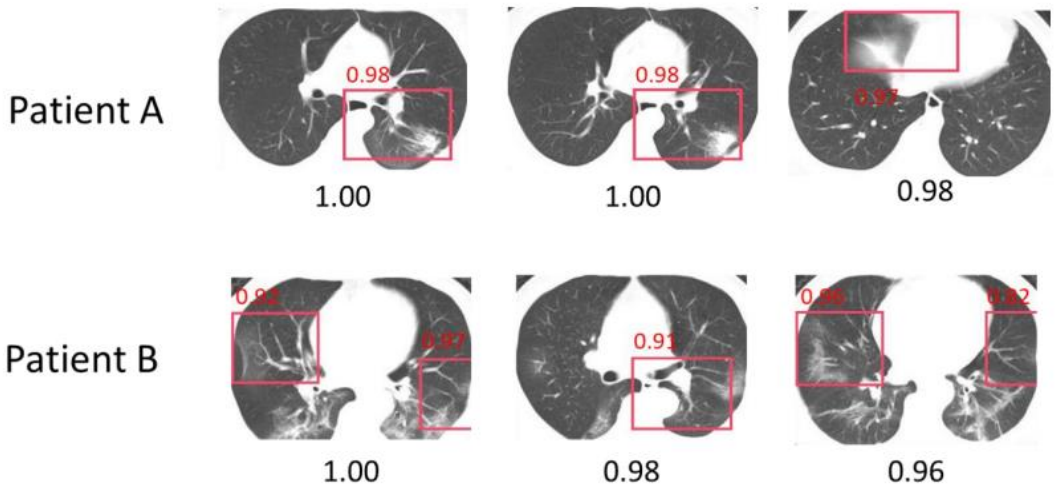


Figure 4(a): Visualization of two correctly diagnosed nCOV-19 Pneumonia patients

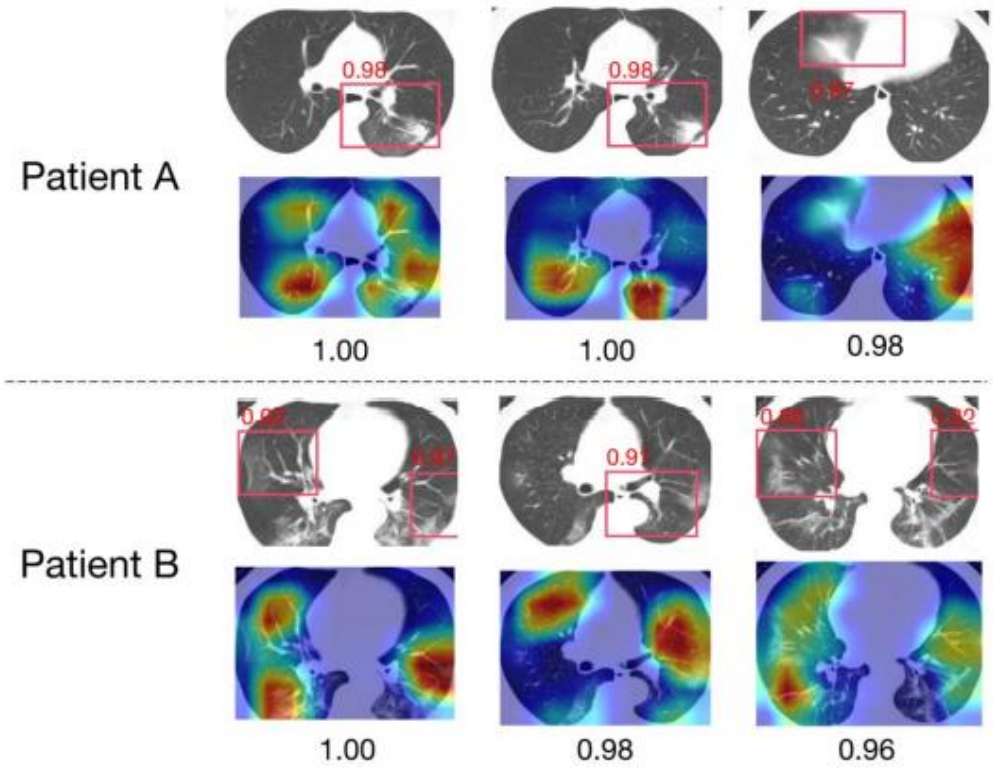


Figure 4(b): Visualization of two correctly diagnosed nCOV-19 Pneumonia patients with heat map

CONCLUSION

CONCLUSION

The study demonstrated the feasibility of a deep learning approach to assist doctors to detect the patients with COVID – 19 and automatically to identify the lesions from CT images. By achieving a high performance on both the pneumonia detection and classification tasks, the proposed system may enable a rapid identification of patients.There are also several weakness points in our work. One major problem is the dataset. We accomplished the work at the very early stage of the COVID pandemic, where there are only very few samples to build such a deep learning prototype. Secondly, due to the issue of batch effect, our method achieved good results on the datasets from original source data collection hospital but was not able to predict the external data directly. Fortunately, it can be alleviated by fine tuning the model with the images from target sources. In the future, we may include a pre – trained model with more image sources for more accurate diagnosis of COVID – 19.

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