Deep GRU-CNN model for COVID-19 detection from chest X-rays data

PIR MASOOM SHAH[1,6], FAIZAN ULLAH[1], DILAWAR SHAH[1], ABDULLAH GANI (SENIOR MEMBER, IEEE)[2,3], CARSTEN MAPLE (MEMBER, IEEE)[4,5], YULIN WANG[6], SHAHID[1], MOHAMMAD ABRAR[7], SAIF UL ISLAM[8]

[1]Department of Computer Science, Bacha Khan University, Charsadda 24000, Pakistan.
[2]Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur 50603, Malaysia
[3]Faculty of Computing and Informatics, University Malaysia Sabah, Labuan 88400, Malaysia
[4]Secure Cyber Systems Research Group, WMG, University of Warwick, Coventry CV4 7AL, U.K
[5]Alan Turing Institute, London NW1 2DB, U.K
[6]School of Computer Science, Wuhan University, Wuhan 430072, China
[7]Department of Computer Science, Mohi-ud-Din Islamic University, Nerian Sharif 12080, Pakistan
[8]Department of Computer Science, Institute of Space Technology, Islamabad 44000, Pakistan

Corresponding authors: Carsten Maple (cm@warwick.ac.uk); Abdullah Gani (abdullahgani@ums.edu.my) and Yulin Wang (yulinwang@whu.edu.cn)

ABSTRACT In the current era, data is growing exponentially due to advancements in smart devices. Data scientists apply a variety of learning-based techniques to identify underlying patterns in the medical data to address various health-related issues. In this context, automated disease detection has now become a central concern in medical science. Such approaches can reduce the mortality rate through accurate and timely diagnosis. COVID-19 is a modern virus that has spread all over the world and is affecting millions of people. Many countries are facing a shortage of testing kits, vaccines, and other resources due to significant and rapid growth in cases. In order to accelerate the testing process, scientists around the world have sought to create novel methods for the detection of the virus. In this paper, we propose a hybrid deep learning model based on a convolutional neural network (CNN) and gated recurrent unit (GRU) to diagnose the virus from chest X-rays (CXRs). In the proposed model, a CNN is used to extract features, and a GRU is used as a classifier. The model has been trained on 424 CXR images with 3 classes (COVID-19, Pneumonia, and Normal). The proposed model achieves encouraging results of 0.96, 0.96, and 0.95 in terms of precision, recall, and f1-score, respectively. These findings indicate how deep learning can significantly contribute to the early detection of COVID-19 in patients through the analysis of X-ray scans. Such indications can pave the way to mitigate the impact of the disease. We believe that this model can be an effective tool for medical practitioners for early diagnosis.

INDEX TERMS Medical data, Deep learning, CNN, GRU, COVID-19, Chest X-rays

I. INTRODUCTION

Artificial Intelligence (AI) applications for data analysis have revolutionized the medical field by achieving human-level accuracy in medical image classification [1]. Coronavirus disease or COVID-19 is a new type of contagious disease caused by a novel strain of flu virus. According to the world health organization (WHO), the first case of COVID-19 was first reported in the Chinese province Wuhan in December 2019 [2]. Coronavirus is recognised as the biggest global challenge in the 21st-century so far [3] [4]. On March 11, 2020 World Health Organization (WHO) declared the novel COVID-19 as a pandemic [5, 6].

Like other infectious diseases in the family of coronavirus, such as Middle East respiratory syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS), COVID-19 infects the main respiratory organs of the human body [7, 8]. A patient infected with COVID-19 experiences symptoms such as coughing, fever, sore throat, tiredness, loss of taste and

The associate editor coordinating the review of this manuscript and approving it for publication was Muhammad Khurram Khan

1

smell [9]. In many cases, infected patients have difficulty in breathing, kidney failure and chest pain, which may result in death [10]. Millions of people have lost their lives worldwide [11]. A number of pharmaceutical companies have achieved success in developing COVID-19 vaccines and numerous trials on humans have been completed or are in progress globally.

The detection of the infected people is a high priority in the battle to conquer this pandemic. According to the Chinese government, the detection of COVID-19 through gene sequencing can be performed using Reverse Transcription Polymerase Chain Reaction (RT-PCR) [12] [13]. Typically, this procedure requires four to six hours to achieve a complete result. Since this disease has spread over a large population, it becomes difficult for a testing laboratory to entertain a large number of tests and provide timely diagnosis [14]. Many patients remain undiagnosed and become a source of spreading the virus. Given the severity of the problem, there is a need for developing fully automated and time-efficient systems.

The early detection of COVID-19 can reduce the spread, and hospital load [15]. As discussed earlier, the RT-PCR testing producer has limitations. As such, the research community is investigating alternative solutions. X-ray and Computed Tomography (CTs) are two medical imaging techniques that have proved effective in detecting lung-related diseases. These techniques have also achieved promising results in the visualization of COVID-19 lung infection [16]. However, when a radiologist or other medical practitioner views the X-ray image, it is possible they may miss early signs of COVID-19. Further, there is a possibility that different experts may come up with a different conclusions.

Recently there has been an increase in medical diagnoses through automated processes. Machine learning algorithms have shown higher accuracy in the detection of several diseases than domain experts. In recent years, Chexnet [17] beat human vision in terms of thoracic disease classification through chest X-rays. Further, PirShah [18] applied CNN on Magnetic Resonance Image (MRI) data to detect Parkinson's disease and achieved state of the art accuracy. In the same way, different researchers have attempted to use CNN for COVID-19 detection from chest X-rays [19]. Ozturk et al. [20] elaborated the importance of the early recovery of the COVID-19 positive patients. They have discussed methods for the detection of the virus. They find that detection of COVID-19 in patients through Computed Tomography and X-rays has been discussed in detail, and that these are useful for timely detection. The authors claim that detection is first performed in binary decision, that is COVID or Non-COVID. In the second approach, the detection is a multi-class classification which is COVID vs Non-COVID vs pneumonia. They have used a data set of 125 X-ray images for their experiments and have obtained an accuracy of 98% for binary while 87% for the detection of COVID-19 disease in a multi-class setting. Inspired by their research, there is a need for a more robust model to diagnose COVID-19 from chest X-rays.

Nguyen et al. developed a hybrid model combining GRU and CNN for handwritten digit recognition which achieved encouraging results in terms of accuracy [21]. We adopted the same strategy of combining CNN and GRU for the detection of COVID-19. CNN is used for feature extraction, while GRU is used as a fully connected layer. Since COVID-19 is a novel disease there is limited data publicly available for experiments. The data set used for this study is obtained from two different sources. COVID -19 infection Xrays are obtained from [22] while pneumonia and normal images are acquired from the Kaggle repository [23]. Previously many deep learning models have been applied to COVID-19 datasets. However, the limited size of datasets presents a challenge. In particular, CNN suffers from a weight vanishing problem with limited data. To address this issue , GRU and LSTM have been previously deployed. We adopt propose a similar framework. To the best of our knowledge, it is the very first attempt to use GRU for Covid-19. The main contributions in this paper are as follows:

1) Proposition of a hybrid deep learning model based on convolutional neural network (CNN) and gated recurrent unit (GRU) for diagnosing COVID-19 from chest X-rays (CXRs).
2) We utilised a CNN with ten convolutional layers and five max-pooling layers for feature extraction from chest X-ray images.
3) To overcome the weight vanishing problem with limited data, we used a GRU for classification.
4) We visualize the decision of the proposed model on X-rays using CAM.

This paper is organized as follows: In section II, related studies are reviewed. Section III presents the building blocks of a convolutional neural network, while section IV discusses the proposed technique in detail. Performance evaluation of the proposed technique is presented in section V before section VI concludes the paper.

II. RELATED WORK

In recent years many researchers have proposed AI algorithms to address medical related issues. Algorithms based on deep learning are now being used in several domains [36, 37, 38]. By utilizing Convolution Neural Network (CNNs) researchers are able to achieve promising results in the field of medicine, including brain tumor segmentation, breast cancer detection, thoracic disease classification in X-ray images and so on. Several strategies for disease detection from biomedical imaging data have already been proposed by various scholars. M Sharma [39] highlighted the key and future challenges of medical image processing. Lee [40], describes a number of studies for the detection of various diseases through the use of deep learning algorithms. Cho et al. [30] proposed a deep learning algorithm for dermatologist-level classification of malignant lip diseases using deep convolution neural network. The author trained the ResNet model on a dataset of 1629 clinical images. The performance of the proposed method was evaluated using different sets of

TABLE 1: Summary of related work

Ref and year	Author	Data set type	Method	Results			
				ACC	SN	SP	AUC
[24] 2017	Yao et al.	X-rays	DenseNet	–	–	–	79
[25] 2019	Rajaraman et al	X-rays	Modified CNN	96	97	96	99
[26] 2019	Peng et al.	CTs	Markov Random Fields	93	–	–	–
[27] 2019	Baltruschat et al	X-rays	ResNet,	–	–	–	80
[28] 2019	Nasrullah et al	CTs	CMixNet	94	94	91	–
[29] 2019	Stephen et al	X-rays	Customized CNN	93	–	–	–
[30] 2020	Soo Ick et al	clinical photos	ResNet	–	75	80	82
[31] 2020	Lei et al	MRI	3D-DSC	76	–	–	–
[32] 2020	Hashmi et al	X-rays	Weighted Classifier	98			99
[33] 2020	Jaemin et al	Image dataset	Customized Deep Learning	–	–	–	96
[34] 2020	Khatri et al	X-rays	EMD	83	–	–	–
[10] 2020	Goyal et al	X-rays	VGG16,VGG19, Restnet50	98	99	99	
[35] 2020	Apostolopoulos et al	X-rays	CNN(Transfer learning)	96	98	96	–

images having 281 and 344 instances. The proposed model is compared with 44 participants for classification purposes. Qu et al. [31] suggested a novel 3D dense separated convolution (3D-DSC) module for volumetric medical image analysis. In this study the traditional 3D convolutional kernels are replaced with 3D-DSC. The 3D-DSC architecture is assembled using a series of densely attached 1D filters.

Hashmo et al. [32] used deep transfer learning techniques for efficient pneumonia detection in chest X-ray images. A novel ensemble approach based on a weighted classifier is introduced. The proposed model merges the prediction results of a weighted classifier from the state of art deep learning algorithms. Son et al. [33] presented a deep learning algorithm for validation and development for detecting multiple anomalies findings in retinal fundus images. Baltruschat [27] developed a deep learning approaches comparison for multi-label chest X-rays classification. In this study transfer learning with and without fine tuning is utilized.

In Xue et al. [26], X-ray images of chest are passed through a process of evaluation, called optimization of scan lines, to remove all parts of the body to minimize error during diagnosis. They address an issue that traditional methods for image restoration suffer when finding locally optimal solutions rather than global, thereby achieving low accuracy results. They also address the issue of high computational load requirements in 4D CT picture registration.

Nasullah et al. [28] developed a modified technique based on a pair of deep, customised three dimensional mixed link networks (CMixNet) for classification and detection of lung cancer. Nodules of lungs were classified using a gradient boosting machine (GBM) by utilizing extracted features from the CMixNet module. The results of deep learning nodule based classification were compared with several factors including patient family history, history of smoking, age, clinical biomarkers, location and size of detected nodule. Yao et al. [24] modeled two different algorithms, long short term memory network and DenseNet, to extract anomalies and dependency. In this study author suggested a two stage end-to-end neural network algorithms that merge a densely attach picture encoder to a recurrent neural network decoder.

Recently several researchers have worked on classification

of pneumonia. Khatri et al [34] suggested to utilize earth movers distance (EMD) algorithm to classify non-infected and infected lungs. Preprocessing is performed on the source image to remove all non-lung areas. The preprocessed image is then resized, normalized by intensity so that a set of uniform shape/size of each lung is obtained. Stephen et al. [29] develop an efficient deep learning approach for classification pneumonia. This study utilizes a CNN model to train for the detection and classification of pneumonia from chest X-rays dataset. To overcome the issue of overfitting and enhance generalization of the model, several data augmentation techniques are used to enhance the quality and size of the dataset. Goyal et al [10] utilize a convolution neural network algorithm to extract important features and perform classification of pneumonia and COVID-19. The dataset used in this study consisted of 748 images having three different class types. The classes are bacterial pneumonia, normal and COVID-19. Three different deep learning algorithms Restnet50, VGG16 and VGG19 were applied to perform classification. Rajaraman et al [17] make an effort to explain the performance of modified CNN to classify pneumonia and also detect difference between viral and bacterial disease in pediatric CXRs. Classification of pneumonia from CXRs is a difficult job due to the presence of huge number of variables that are extraneous to pneumonia diagnosis.

The early detection of COVID-19 is essential for the timely isolation of patients to prevent spreading of the virus. In practice many methods have been slow and costly, therefore automatic detection is required. Detection of COVID-19 from X-ray images has been performed by Apostolopoulos et al in [41]. They utilized two datasets with 1427 images and 1442 images. These datasets are collected from publicly available repositories. Accuracy, sensitivity and specificity of the system using deep learning with transfer learning is 96%, 98% and 96% respectively. According to the authors, detection of COVID-19 via X-rays is a useful addition to the traditional testing methods.

Abdulkareem et al. [42] suggested a model based on the Internet of Things (IoT) and Machine Learning (ML) to diagnose COVID-19 patients in a smart hospital. The author suggested the use of ML to analyze laboratory find-

ings can improve the accuracy rate of diagnosis (classification). Three different machine learning techniques, namely Random Forest (RF), Support Vector Machine (SVM) and Naive Bayes (NB), were utilized on a public dataset. The authors claim that they achieved up to 95% accuracy using the Support Vector Machine. Dac Nhuong Le et al. [43] proposed a novel IoT-enabled deep support vector machine (DSVM) and Depthwise separable convolution neural network (DWS-CNN) to classify COVID-19 disease. The DWS-CNN model detects both multiple and binary classes of COVID-19. Gaussian Filtering (GF) was used to preprocess and extract features. The DWS-CNN model is employed for replacing default convolution networks for automatic feature extraction. The diagnostic outcome of the DWS-CNN model is tested using a chest X-ray (CXR) image dataset, and the results are investigated in terms of different performance measures. They have claimed a level of 99.06% and 98.54% accuracy. Waheed et al. [44] proposed a novel technique CovidGAN to generate synthetic chest X-ray (CXR) images by using Auxiliary Classifier Generative Adversarial Network (ACGAN). The author claimed that synthetic images generated from CovidGAN could improve the performance of CNNs to detect COVID-19 disease. Their results show an 85% accuracy achieved by using a traditional neural network. After adding synthetic images generated from CovidGAN, the overall accuracy rose to 95%. Pinter et al. [45] proposed a hybrid-based model to predict COVID-19. The algorithm integrated a multi-layered perceptron-imperialist competitive algorithm (MLP-ICA) and adaptive network-based fuzzy inference system (ANFIS). This was used to predict the time series of mortality rate and infected individuals. Validation of the proposed method is performed using patient data over 9 days with promising results. Mahanty et al. [46] suggested a traditional convolution neural network algorithm for binary classification of pneumonia-based conversion of VGG-19. A decision tree and InceptionV2 are applied over a dataset of CT scan image and X-ray dataset, containing 360 images. The authors claim that the fine-tuned version of the proposed model can achieve training and validation accuracy of 91%. Dansana et al. [47] propose research using an exponential model (SIR) and two non-linear growth models (Gompertz, Verhulst) to analyze the coronavirus pandemic across the world. Data used in this research is collected from the John Hopkins University repository over a time span of Jan 30, 2020, to June 4, 2020. The proposed model performs better than the three previous models with an R-score of 0.9981. The summary of related work is presented in table 1.

III. CONVOLUTIONAL NEURAL NETWORK
CNN has shown record performance in several domains such as image classification [48, 49], speech recognition [50], face recognition [51], language translation [52], semantic segmentation [53], image captioning [54], medical image analysis [55, 56], machine translation and other vision tasks. Typically, a CNN consists of convolution, pooling, and dense layers. In the following subsection we explain the building

blocks of typical CNN models.

A. CONVOLUTION LAYER
The first layer of a CNN is the convolutional layer. It extracts features from an input image with the help of a kernel and produces a feature map (convoluted image) as output. A convolutional operation is composed of several elements including the kernel or filter (kernel matrix), input image (input matrix), and feature map.

B. KERNEL
The kernel is a matrix that is small n relation to the input matrix (input image) and consists of real values. The kernel takes a patch from the input image in specific dimensions (equal to the kernel dimension) and applies a dot operation on the patch and kernel values resulting in a single entry in the feature map. The patch selection is then moved to the right or down-word depending on stride movement. This operation is continued until the whole image is complete; the values of the kernel change after each iteration during training. The final goal is to help the model to achieve the highest accuracy and lowest optimization loss. Therefore, this operation ends-up with learning different features such as edges or color-related features.

C. ACTIVATION FUNCTION
Typically, the convolution operation generates linear output. In order to avoid linearity, we use an activation function, which makes the network universal function approximator. Several activation functions are proposed such as sigmoidal, tangent, Rectified Linear Unit (ReLU). Relu is the most widely used as it converts negative values to zero. The mathematical model can be seen in equation 1.

$$f(x) = \max(0, x) \tag{1}$$

D. POOLING
Pooling layers are responsible for reducing the dimensionality of feature maps in a CNN. Several pooling layers are proposed, which include: Max-pooling, Average-pooling, and Sum-pooling. However, Max-pooling showed high performance and widely used for dimensionality reduction. Max-pooling picks the maximum value from the matrix and avoids the rest of the values. The mathematical formulation of Max-pooling is stated in equation 2.

$$pool_{i,j} = \max_p f'(x)_{i+p,j+p} \tag{2}$$

where i and j represent spatial position.

E. FULLY CONNECTED LAYERS
Softmax activation is a widely-used activation function for the performance of deep learning approaches. Equation 3 shows the mathematical equation for the softmax function.

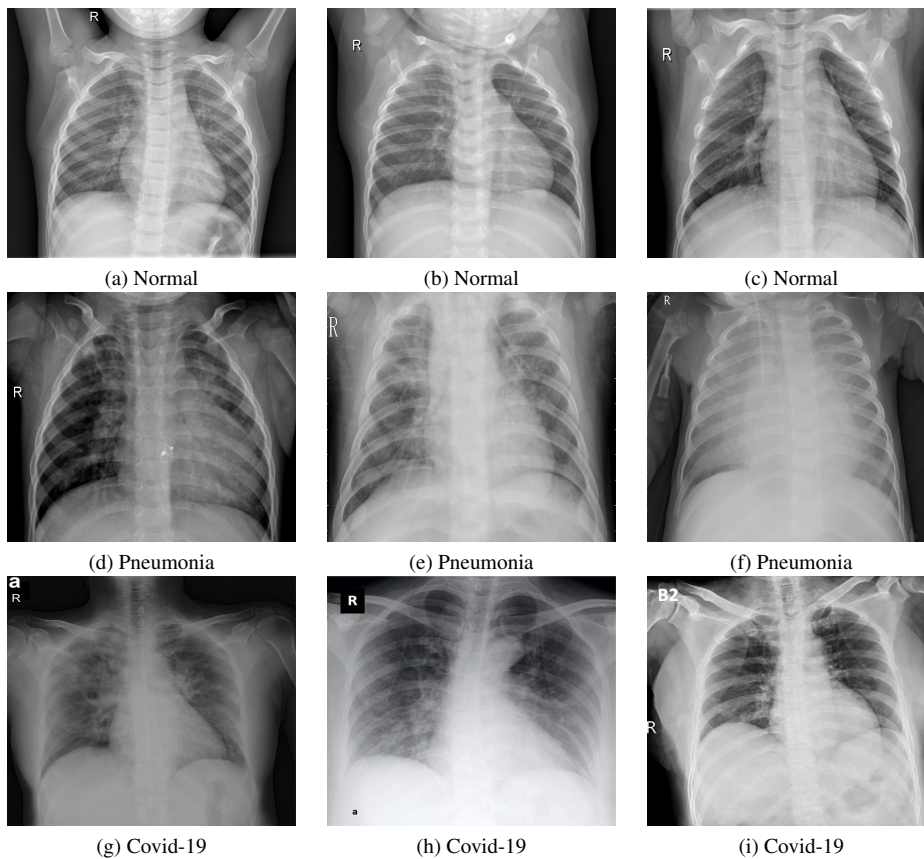$$Softmax(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{3}$$

FIGURE 1: From Top to Bottom row wise: Presents normal, pneumonia and Covid-19 X-ray images

1) Regularization

Deep neural networks with high learning parameters and lower or noisy training data can suffer from overfitting problems. Overfitting refers to phenomena when the model performs better on training data, but it fails to classify new test instances belonging to the same domain problem. To avoid this issue, we used dropout strategy. During training, the dropout randomly drops neurons with probability p in fully-connected layers. The workflow of the dropout is formulated in equation 4.

$$y_j = \sum_{M \, \epsilon \, M^*} Pr(m) y_j^M \qquad (4)$$

In the above equation y_j is the expected unit j, M^* is the set of all thinned network while y^M is the output of the unit M. $Pr()$ is the probability function in the above equation.

2) Loss Function

The loss or cost function compares the target output and predicted output. It normally minimizes during the training phase. The model is said to be a good learner and near to global minima when its loss value falls to a minimum. We used categorical cross-entropy as the loss function. Its formulated version can be seen in equation 5.

$$f_{cost}(x) = - \sum_{j \, \epsilon \, voxels} \sum_{k \, \epsilon \, classes} c_{j,k} \, \log(\hat{c}_{j,k}) \qquad (5)$$

Where c represents the true target class and $\hat{c}$ shows the predicted class.

IV. PROPOSED METHODOLOGY

We used a CNN and a GRU on open-access datasets in this research. We obtained three classes of CXR scans from the two sources: COVID-19, Normal, and Pneumonia. We then split the entire dataset into 3 sets: training, validation, and testing. To determine the models' final classification accuracy, we kept the test split separate (i.e., did not include CXR in the training set). We used a deep convolutional neural network (CNN) for feature extraction while GRU for classification. Figure 3 shows the framework of the proposed method. The methods are stepwise explained in the below sections.

A. DATASET

The datasets used in this research has been acquired from two different sources. Since COVID-19 is a novel disease, therefore, such datasets are of limited availability for research experiments. In this regard, we approached two different repositories, Joseph Paul Cohen and the Kaggle repository. The acquired dataset from these two repositories consists of
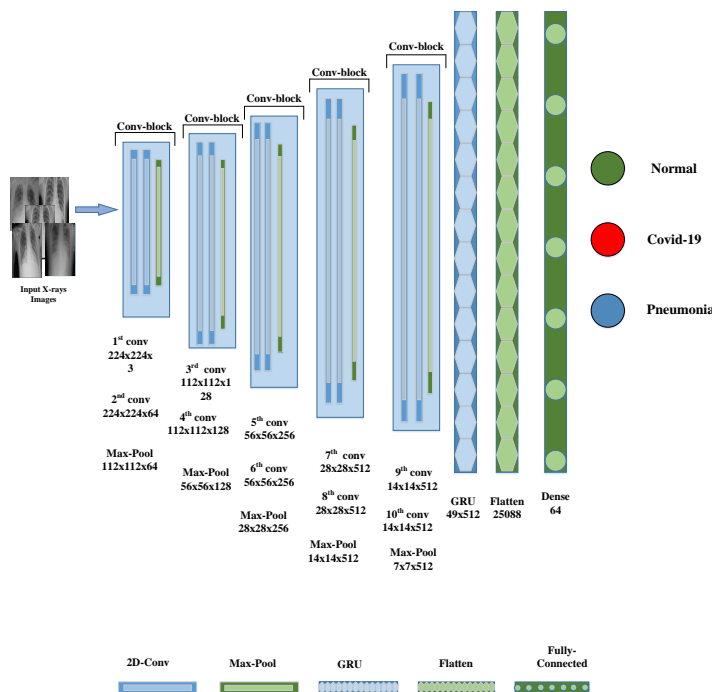
FIGURE 2: The building blocks of the proposed CNN-GRU model.

TABLE 2: Data Distribution

Data Division sets	Covid-19	Normal	Pneumonia	Total
Training	99	98	99	296
Validation	14	15	14	43
Testing	29	28	28	85

424 X-ray images and three classes. To ensure the balance between classes, we extract an equal number of instances (141) for every class. The dataset is further divided into three sets training, validation, and testing set with the ratio of 70%, 10%, and 20%, respectively. Figure 1 shows the sample of the considered dataset, while table 2 represents the dataset distribution.

1) Pre-processing

The X-ray images were first passed into the pipeline for preprocessing. In the preprocessing pipeline, data resizing, shuffling, and normalization are performed. The output images were then forwarded to the system for feature extraction.

2) Feature extraction

Any deep learning model can be easily integrated into our model for feature extraction, but our customized model with defined layers learned best-fit features related to COVID-19 and pneumonia. We also tried added and subtracted the convolutional layers. However, by doing this, our results

were then compromised. The figure represents the feature extraction process. Where each image (CXR) is passed through the convolutional layers. The convolutional layer transforms the image into several dimensions (n is the number of defined channels) to feature maps. The first convolutional block receives the input images (X-rays) of 224x224 in three channels (224x224x3). The 224x244 represents the height and width, while 3 represents the image dimensions like Red, Green, Blue (RGB). This block generates 64 feature maps in 122x122 dimensions, further reduced by the max-pooling layer to 112x112x64. Similarly, the second convolutional block receives 122x122 input of dimension 64 and produces the features maps of the dimensions 11x112x128, which is further reduced by a second max-pooling layer 56x56x128. In the same way, these feature maps are passed through 3rd, 4th, and 5th convolutional blocks. The final feature maps were obtained in the dimensions of 7x7x512, which are further fed to GRU for classification.

3) Gated recurrent unit

Typically Deep Neural Networks (DNNs) have the problem of short-term memory. In back-propagation, the gradients may shrink with time, and thus the problem of vanishing gradient occurs. Gradients are values used to update the weights during back-propagation. When the gradient value becomes small, then it may not contribute in learning. There-
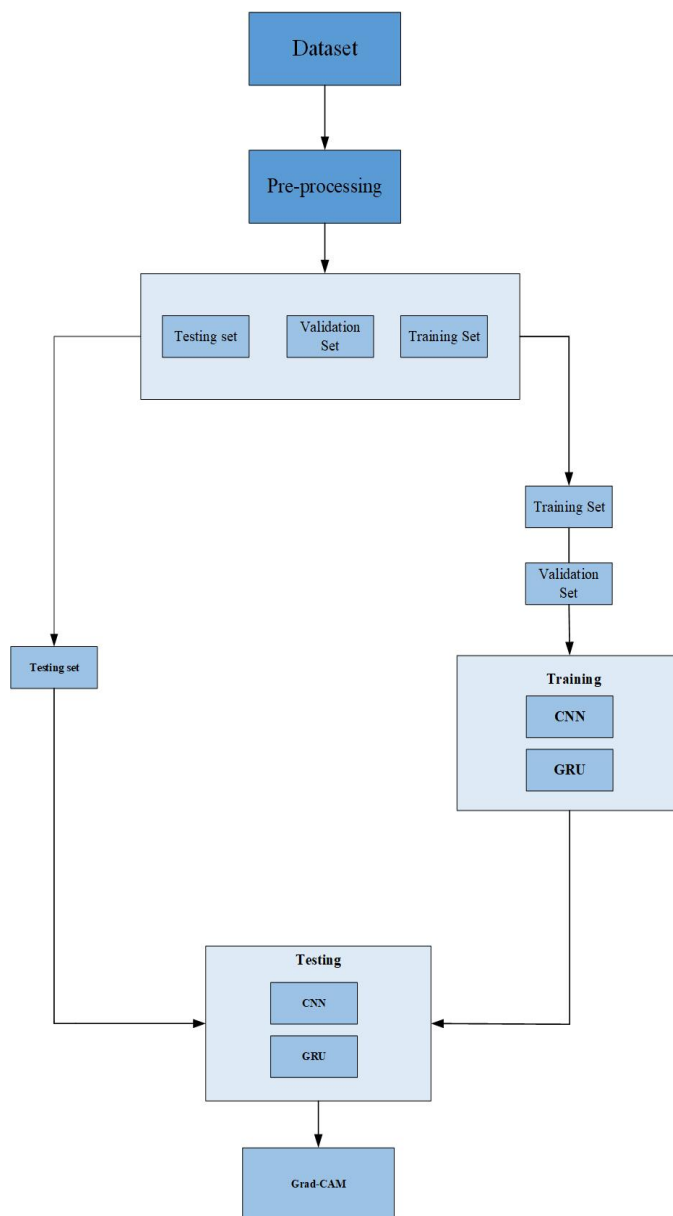
FIGURE 3: Work flow of the proposed method.

fore, when a layer in RNN receives a small value gradient, then it may stop learning. To tackle this problem, GRU is the best option. This mechanism can handle the problem of short-term memory. GRU is a simple and new generation of RNN. It consists of two gate reset and update gates. The reset gate is working as a barrier. The decision of keeping or discarding the data is a concern to update the gate, while the reset decides how much previous information should be kept.

4) The Detail Summary of the Model

To better understand the proposed architecture, we have divided our network into several blocks; Conv-block, GRU-block, and FC-block. In total, we have 5 Conv-blocks, 1 GRU-Block, 1 FC-block. Every Conv-block consists of two convolutional layers, while in each block, the last convolutional layer is followed by a max-pooling layer. However, the number of parameters and filters remains disparate in every block.

The output of the last conv-block is then forwarded to GRU-Block to extract time information. To predict the disease, the information is then fed to the last FC-block, which consists of convolutional layers with softmax function. Figure 2 illustrates the architecture of the proposed system.
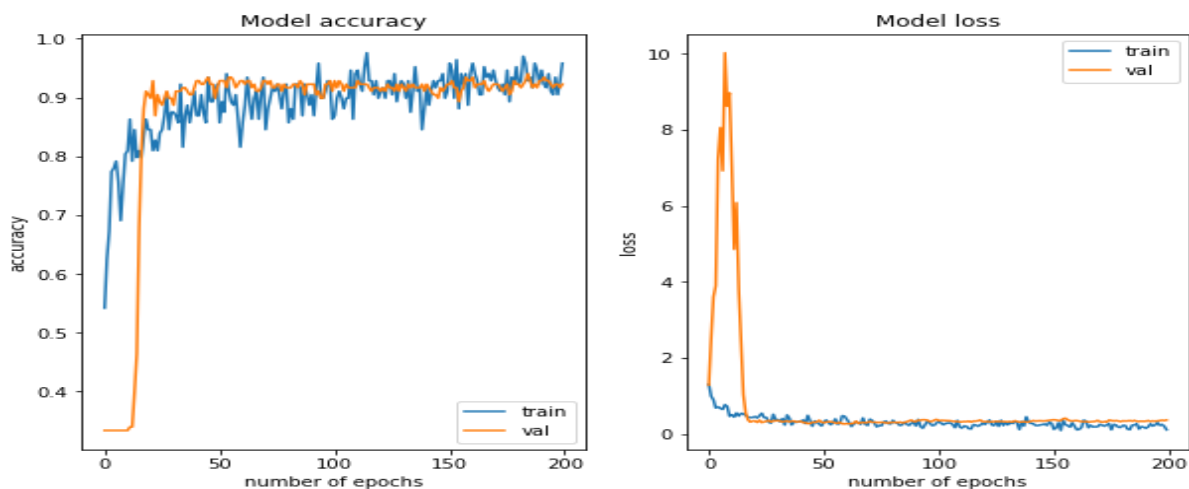
V. PERFORMANCE EVALUATION

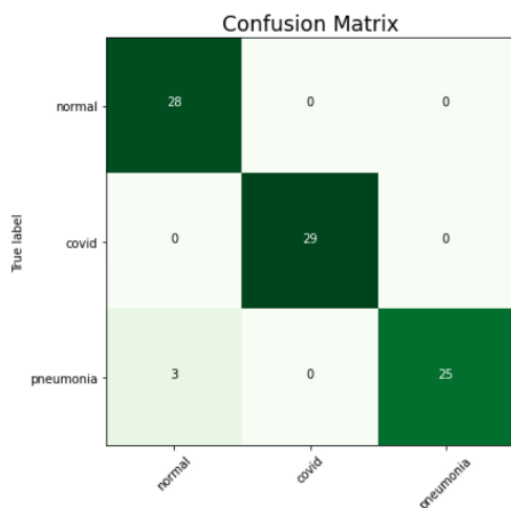FIGURE 4: Training Accuracy and Training Loss

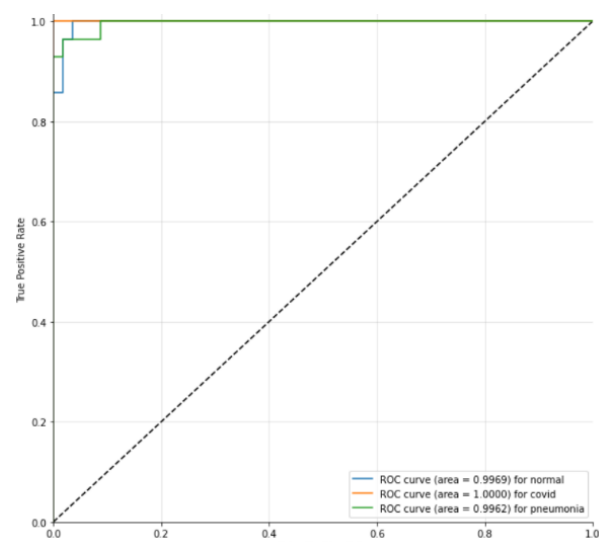FIGURE 5: Confusion Matrix

FIGURE 6: Receiver Operating Characteristic

A. EXPERIMENTAL SETUP

The dataset is split into training validation and testing set with the ratio of 70%, 10%, and 20%, respectively. All the experiments were carried in a Kaggle notebook. The GRU-CNN model is trained and tested using Keras with TensorFlow backend. The experiments were made on maximum epochs 200, with a batch size of 40, and before the softmax classification layer, the dropout layer with 0.5 dropout probability was added. The learning rate is set to 3e-4, while learning rate decay is set to 0.95. The sample code of deep GRU-CNN model is available online at [1].

B. TRAINING AND VALIDATION PHASE

Figure 4 illustrates the proposed model's performance in the training and validation phase in terms of accuracy and

[1]https://colab.research.google.com/drive/1oyHSleBdz85cH4lyUmfFBGhs_pGgKYI7?usp=sharing

loss. The orange line represents validation accuracy in the model accuracy plot, while the blue line represents training accuracy. Similarly, in the Model loss plot, the training loss is signified by the blue line, whereas validation is presented in the orange line. The obtained training and validation accuracy on the 200th epoch is 96% and 93%, respectively. In the same way, training and validation loss on the 200th epoch is 0.8 and 0.9, respectively.

The performance of the proposed model of the test phase is shown in figure 5 in terms of confusion matrix. The first row and column represent instances in normal class, while the second and third show COVID-19 and pneumonia classes. The proposed model classified all the normal and COVID-19 instances correctly. However, in the pneumonia class, among 28 images, only 3 images were miss-classified as normal, whereas the rest of 25 images are correctly classified as pneumonia.
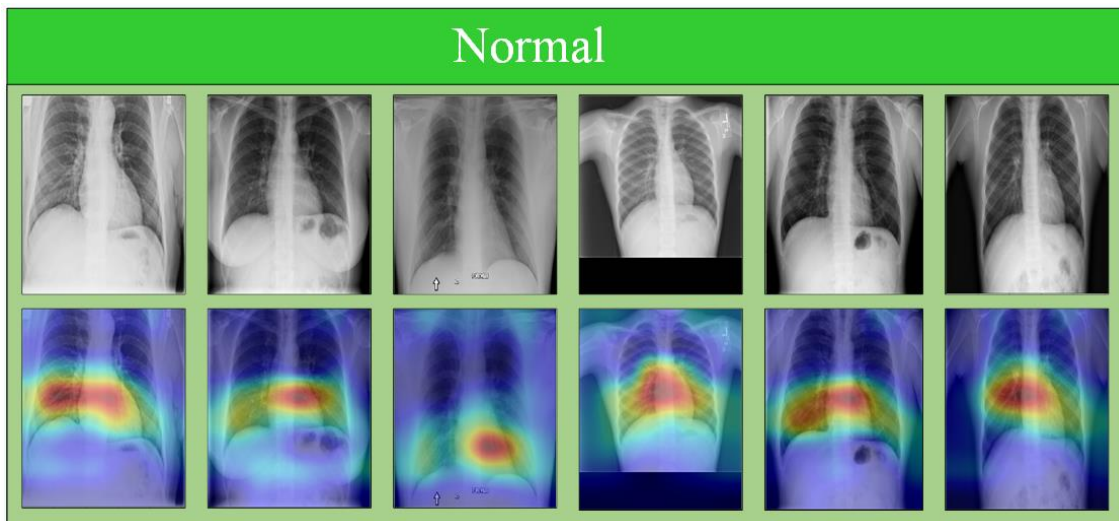
FIGURE 7: Normal True Negatives: correctly classified normal X-ray scans with corresponding attention maps (CAM). The figure is best viewed in color.
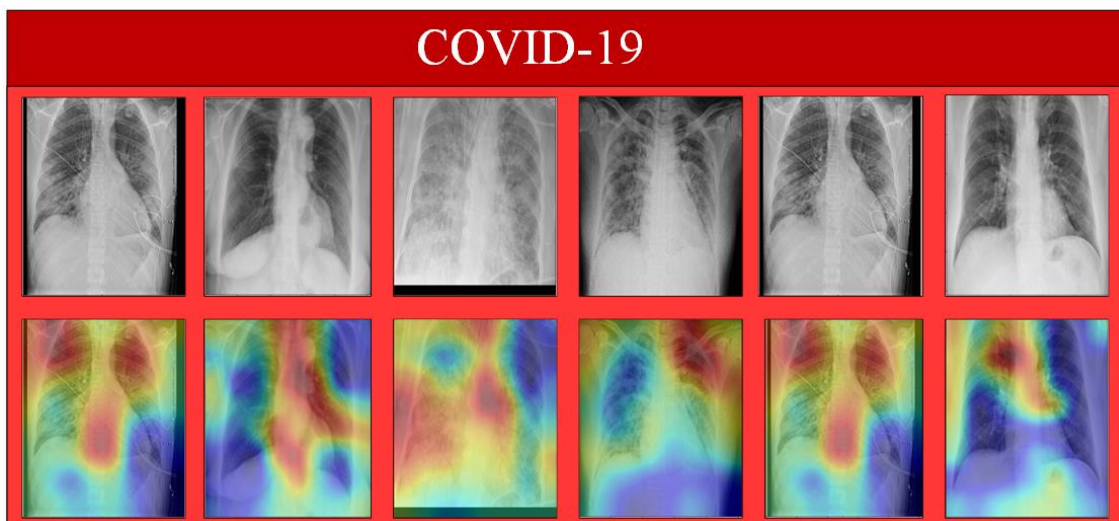

FIGURE 8: Covid-19 True Positives: correctly classified Covid-19 X-ray scans with corresponding attention maps (CAM). The figure is best viewed in color.

Table 3 shows the precision, recall, and f1-score for each case in the test set. GRU-CNN achieved 0.9 precision 1.00 recall and 0.95 f1-score for normal class. For COVID-19 precision, recall and f1-score are recorded 1.00, 1.00, 1.00, respectively. In the case of pneumonia, the precision, recall, and fi-score are 1.0, 0.89, 0.94, respectively. Among all the scores, the highest score is recorded in the COVID-19 class, while the lowest results values were found in the pneumonia class. The mean score for all the classes are recorded as 0.96, 0.96, and 0.95 in terms of precision, recall and f1-score.

In the same way, Figure 6 represents the ROC curve (receiver operating characteristic curve) for all the classes. It can be seen that class COVID-19 achieved the highest ROC score of 1.00, followed by The Normal class, which is

TABLE 3: Results of the proposed CNN-GRU for individual Normal, Covid-19 and Pneumonia in terms of Precision, Recall and F1-score

Labels	Precision	Recall	F1-score	Support
Normal	0.90	1.00	0.95	28
Covid-19	1.00	1.00	1.00	29
Pneumonia	1.00	0.89	0.94	28

0.9969. While the class Pneumonia archived the least score of 0.9969. Such results indicate that our model has learned the discriminate features for all the classes.
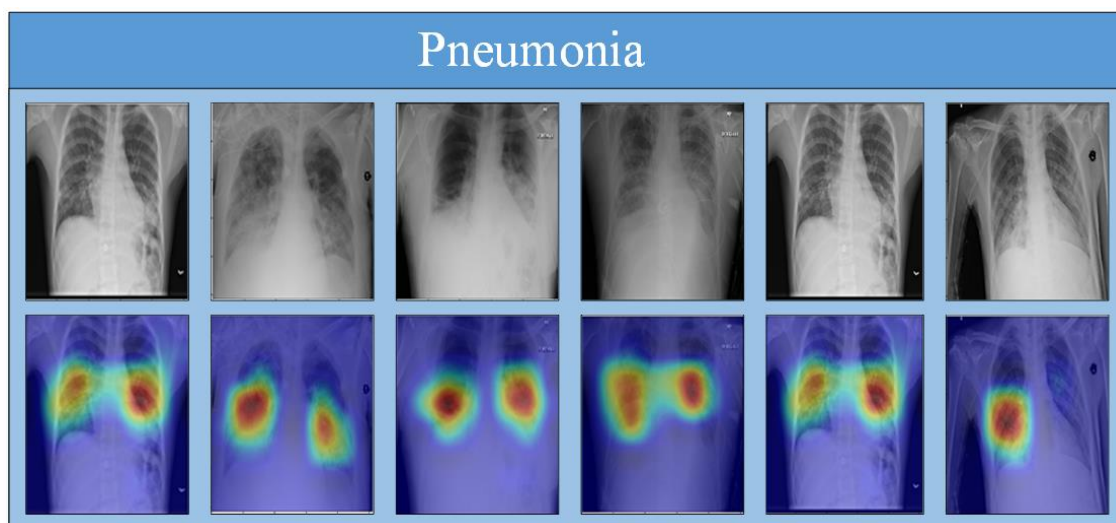
FIGURE 9: Pneumonia True Positives: correctly classified pneumonia X-ray scans with corresponding attention maps (CAM). The figure is best viewed in color.

C. GRAD-CAM

Developing a more robust understanding of deep learning models is an important field of study. Deep Convolution Neural Networks are also referred to as black-box models due to limited knowledge of their internal behavior. An attempt to create more dynamic and explainable deep learning models. Recently, a number of researchers have suggested methods to include class activation maps (CAMs) that represent deep learning predictions with the goal of helping human experts develop intelligible deep learning models. In this regard, the author's proposed methods to produce gradient-based CAM (i.e., grad-cam) in [57], which highlights the more descriptive input picture relating to the final model prediction for each class. In developing trustworthiness in deep learning-based algorithms, the availability of such information, along with the model's predictions, plays a vital role. In addition, the existence of the grad-cam enables a human expert (doctor) to verify the efficiency of deep learning.

To provide a comparative understanding of the model's predictions, we also visualize the normal class's attention maps. The input image, model estimation, and corresponding Grad-Cams of the proposed model, for normal class, are shown in figure 7. In figure 7, the first row represents correctly classified normal X-ray images from the normal class while the second row represents the Grad-Cams against each image. Similarly, in figure 8, 9 shows model Grad-Cams and model prediction for COVID-19 and pneumonia respectively.

The proposed system comes up with limitations like this model is only limited to the X-rays posterior-anterior (PA) view. Therefore, other views of X-rays such as anterior-posterior (AP), lateral and other factors cannot be evaluated. Due to the availability of limited data, our model is trained and tested on minimal data. Lastly, the model performance comparison is only performed with previous algorithms; comparison with human domain experts like radiologists is

avoided.

VI. CONCLUSION AND FUTURE WORK

As cases of COVID-19 are rising rapidly, many countries are turned into lockdown and facing a shortage of resources. During this health emergency, it is crucial to detect every single positive case. To overcome the limited testing capacity, we applied a deep GRU-CNN network on the chest X-rays data to detect COVID-19. We used CNN as a feature extractor and GRU as a classifier. By integrating extracted features with GRU, the proposed system's performance is improved in terms of classification between COVID, pneumonia, and normal instances. In the future, we intend to use Generative adversarial models for data augmentation.

REFERENCES

[1] M. Konno and H. Ishii, "Ai for medical use," *Oncotarget*, vol. 10, no. 2, p. 86, 2019.

[2] R. Huang, M. Liu, and Y. Ding, "Spatial-temporal distribution of covid-19 in china and its prediction: A data-driven modeling analysis," *The Journal of Infection in Developing Countries*, vol. 14, no. 03, pp. 246–253, 2020.

[3] A. C. Cunningham, H. P. Goh, and D. Koh, "Treatment of covid-19: old tricks for new challenges," vol. 24, no. 1, p. 91, 2020.

[4] Z. Wang, Y. Xiao, Y. Li, J. Zhang, F. Lu, M. Hou, and X. Liu, "Automatically discriminating and localizing covid-19 from community-acquired pneumonia on chest x-rays," *Pattern recognition*, vol. 110, p. 107613, 2021.

[5] D. Cucinotta and M. Vanelli, "Who declares covid-19 a pandemic," *Acta Bio Medica: Atenei Parmensis*, vol. 91, no. 1, p. 157, 2020.

[6] M. Ndiaye, S. S. Oyewobi, A. M. Abu-Mahfouz, G. P. Hancke, A. M. Kurien, and K. Djouani, "Iot in the wake of covid-19: A survey on contributions, challenges and evolution," *IEEE Access*, vol. 8, pp. 186 821–186 839, 2020.

[7] H. A. Rothan and S. N. Byrareddy, "The epidemiology and pathogenesis of coronavirus disease (covid-19) outbreak," *Journal of autoimmunity*, p. 102433, 2020.

[8] S. Hu, Y. Gao, Z. Niu, Y. Jiang, L. Li, X. Xiao, M. Wang, E. F. Fang, W. Menpes-Smith, J. Xia *et al.*, "Weakly supervised deep learning for covid-19 infection detection and classification from ct images," *IEEE Access*, vol. 8, pp. 118 869–118 883, 2020.

[9] C. Menni, A. Valdes, M. B. Freydin, S. Ganesh, J. E.-S. Moustafa, A. Visconti, P. Hysi, R. C. Bowyer, M. Mangino, M. Falchi *et al.*, "Loss of smell and taste in combination with other symptoms is a strong predictor of covid-19 infection," *MedRxiv*, 2020.

[10] L. Goyal and N. Arora, "Deep transfer learning approach for detection of covid-19 from chest x-ray images," *International Journal of Computer Applications*, vol. 975, p. 8887.

[11] M. Awais, M. Raza, N. Singh, K. Bashir, U. Manzoor, S. ul Islam, and J. J. Rodrigues, "Lstm based emotion detection using physiological signals: Iot framework for healthcare and distance learning in covid-19," *IEEE Internet of Things Journal*, 2020.

[12] I. Kokkinakis, K. Selby, B. Favrat, B. Genton, and J. Cornuz, "Covid-19 diagnosis: clinical recommendations and performance of nasopharyngeal swab-pcr," *Revue medicale suisse*, vol. 16, no. 689, pp. 699–701, 2020.

[13] M. Roberts, D. Driggs, M. Thorpe, J. Gilbey, M. Yeung, S. Ursprung, A. I. Aviles-Rivero, C. Etmann, C. McCague, L. Beer *et al.*, "Common pitfalls and recommendations for using machine learning to detect and prognosticate for covid-19 using chest radiographs and ct scans," *Nature Machine Intelligence*, vol. 3, no. 3, pp. 199–217, 2021.

[14] C.-C. F. Tam, K.-S. Cheung, S. Lam, A. Wong, A. Yung, M. Sze, Y.-M. Lam, C. Chan, T.-C. Tsang, M. Tsui *et al.*, "Impact of coronavirus disease 2019 (covid-19) outbreak on st-segment–elevation myocardial infarction care in hong kong, china," *Circulation: Cardiovascular Quality and Outcomes*, vol. 13, no. 4, p. e006631, 2020.

[15] Y.-W. Tang, J. E. Schmitz, D. H. Persing, and C. W. Stratton, "Laboratory diagnosis of covid-19: current issues and challenges," *Journal of clinical microbiology*, vol. 58, no. 6, 2020.

[16] M. Blain, M. T. Kassin, N. Varble, X. Wang, Z. Xu, D. Xu, G. Carrafiello, V. Vespro, E. Stellato, A. M. Ierardi *et al.*, "Determination of disease severity in covid-19 patients using deep learning in chest x-ray images," *Diagnostic and Interventional Radiology*, vol. 27, no. 1, p. 20, 2021.

[17] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya *et al.*, "Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning," *arXiv preprint arXiv:1711.05225*, 2017.

[18] P. M. Shah, A. Zeb, U. Shafi, S. F. A. Zaidi, and M. A. Shah, "Detection of parkinson disease in brain mri using convolutional neural network," in *2018 24th International Conference on Automation and Computing (ICAC)*. IEEE, 2018, pp. 1–6.

[19] H. S. Maghdid, A. T. Asaad, K. Z. Ghafoor, A. S. Sadiq, and M. K. Khan, "Diagnosing covid-19 pneumonia from x-ray and ct images using deep learning and transfer learning algorithms," *arXiv preprint arXiv:2004.00038*, 2020.

[20] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, "Automated detection of covid-19 cases using deep neural networks with x-ray images," *Computers in biology and medicine*, vol. 121, p. 103792, 2020.

[21] V. Nguyen, J. Cai, and J. Chu, "Hybrid cnn-gru model for high efficient handwritten digit recognition," in *Proceedings of the 2nd International Conference on Artificial Intelligence and Pattern Recognition*, 2019, pp. 66–71.

[22] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images," *arXiv preprint arXiv:2003.11055*, 2020.

[23] A. Stein, "Pneumonia dataset annotation methods. rsna pneumonia detection challenge discussion," 2018.

[24] L. Yao, E. Poblenz, D. Dagunts, B. Covington, D. Bernard, and K. Lyman, "Learning to diagnose from scratch by exploiting dependencies among labels," *arXiv preprint arXiv:1710.10501*, 2017.

[25] S. Rajaraman, S. Candemir, G. Thoma, and S. Antani, "Visualizing and explaining deep learning predictions for pneumonia detection in pediatric chest radiographs," in *Medical Imaging 2019: Computer-Aided Diagnosis*, vol. 10950. International Society for Optics and Photonics, 2019, p. 109500S.

[26] P. Xue, E. Dong, and H. Ji, "High-order markov random field based image registration for pulmonary ct," in *Annual Conference on Medical Image Understanding and Analysis*. Liverpool, UK: Springer, 2019, pp. 339–350.

[27] I. M. Baltruschat, H. Nickisch, M. Grass, T. Knopp, and A. Saalbach, "Comparison of deep learning approaches for multi-label chest x-ray classification," *Scientific reports*, vol. 9, no. 1, pp. 1–10, 2019.

[28] N. Nasrullah, J. Sang, M. S. Alam, M. Mateen, B. Cai, and H. Hu, "Automated lung nodule detection and classification using deep learning combined with multiple strategies," *Sensors*, vol. 19, no. 17, p. 3722, 2019.

[29] O. Stephen, M. Sain, U. J. Maduh, and D.-U. Jeong, "An efficient deep learning approach to pneumonia classification in healthcare," *Journal of healthcare engineering*, vol. 2019, 2019.

[30] S. I. Cho, S. Sun, J.-H. Mun, C. Kim, S. Kim, S. Cho, S. Youn, H. C. Kim, and J. Chung, "Dermatologist-level classification of malignant lip diseases using a deep convolutional neural network," *British Journal of Dermatology*, vol. 182, no. 6, pp. 1388–1394, 2020.

[31] L. Qu, C. Wu, and L. Zou, "3d dense separated convolution module for volumetric medical image analysis," *Applied Sciences*, vol. 10, no. 2, p. 485, 2020.

[32] M. F. Hashmi, S. Katiyar, A. G. Keskar, N. D. Bokde, and Z. W. Geem, "Efficient pneumonia detection in chest xray images using deep transfer learning," *Diagnostics*, vol. 10, no. 6, p. 417, 2020.

[33] J. Son, J. Y. Shin, H. D. Kim, K.-H. Jung, K. H. Park, and S. J. Park, "Development and validation of deep learning models for screening multiple abnormal findings in retinal fundus images," *Ophthalmology*, vol. 127, no. 1, pp. 85–94, 2020.

[34] A. Khatri, R. Jain, H. Vashista, N. Mittal, P. Ranjan, and R. Janardhanan, "Pneumonia identification in chest x-ray images using emd," in *Trends in Communication, Cloud, and Big Data*. New York, USA: Springer, 2020, pp. 87–98.

[35] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks," *Physical and Engineering Sciences in Medicine*, vol. 43, no. 2, pp. 635–640, 2020.

[36] K. Kallianos, J. Mongan, S. Antani, T. Henry, A. Taylor, J. Abuya, and M. Kohli, "How far have we come? artificial intelligence for chest radiograph interpretation," *Clinical radiology*, vol. 74, no. 5, pp. 338–345, 2019.

[37] Y. Zhang, G. Wang, M. Li, and S. Han, "Automated classification analysis of geological structures based on images data and deep learning model," *Applied Sciences*, vol. 8, no. 12, p. 2493, 2018.

[38] Y. Wang, C. Wang, and H. Zhang, "Ship classification in high-resolution sar images using deep learning of small datasets," *Sensors*, vol. 18, no. 9, p. 2929, 2018.

[39] M. Sharma and N. Miglani, "Automated brain tumor segmentation in mri images using deep learning: Overview, challenges and future," in *Deep Learning Techniques for Biomedical and Health Informatics*. New York, USA: Springer, 2020, pp. 347–383.

[40] G. Lee and H. Fujita, *Deep learning in medical image analysis: challenges and applications*. New York, USA: Springer, 2020, vol. 1213.

[41] S. Ahmed, T. Hossain, O. B. Hoque, S. Sarker, S. Rahman, and F. M. Shah, "Automated covid-19 detection from chest x-ray images: A high resolution network (hrnet) approach," *medRxiv*, 2020.

[42] K. H. Abdulkareem, M. A. Mohammed, A. Salim, M. Arif, O. Geman, D. Gupta, and A. Khanna, "Realizing an effective covid-19 diagnosis system based on machine learning and iot in smart hospital environment," *IEEE Internet of Things Journal*, 2021.

[43] D.-N. Le, V. S. Parvathy, D. Gupta, A. Khanna, J. J. Rodrigues, and K. Shankar, "Iot enabled depthwise separable convolution neural network with deep support vector machine for covid-19 diagnosis and classification," *International Journal of Machine Learning and Cybernetics*, pp. 1–14, 2021.

[44] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, and P. R. Pinheiro, "Covidgan: data augmentation using auxiliary classifier gan for improved covid-19 detection," *Ieee Access*, vol. 8, pp. 91 916–91 923, 2020.

[45] G. Pinter, I. Felde, A. Mosavi, P. Ghamisi, and R. Gloaguen, "Covid-19 pandemic prediction for hungary; a hybrid machine learning approach," *Mathematics*, vol. 8, no. 6, p. 890, 2020.

[46] C. Mahanty, R. Kumar, B. K. Mishra, D. J. Hemanth, D. Gupta, and A. Khanna, "Prediction of covid-19 active cases using exponential and non-linear growth models," *Expert Systems*, p. e12648, 2020.

[47] D. Dansana, R. Kumar, A. Bhattacharjee, D. J. Hemanth, D. Gupta, A. Khanna, and O. Castillo, "Early diagnosis of covid-19-affected patients based on x-ray and computed tomography images using deep learning algorithm," *Soft Computing*, pp. 1–9, 2020.

[48] Q. Xie, M.-T. Luong, E. Hovy, and Q. V. Le, "Self-training with noisy student improves imagenet classification," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 10 687–10 698.

[49] P. M. Shah, H. Khan, U. Shafi, S. ul Islam, M. Raza, H. Le-Minh *et al.*, "2d-cnn based segmentation of ischemic stroke lesions in mri scans," in

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3077592, IEEE Access

P. M. Shah *et al.*: Deep GRU-CNN Model for COVID-19 Detection From CXRs Data

International Conference on Computational Collective Intelligence, Da Nang, Vietnam. Springer, 2020, pp. 276–286.

[50] W. Xiong, L. Wu, F. Alleva, J. Droppo, X. Huang, and A. Stolcke, "The microsoft 2017 conversational speech recognition system," in *2018 IEEE international conference on acoustics, speech and signal processing (ICASSP)*. IEEE, 2018, pp. 5934–5938.

[51] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition," University of Oxford, UK, 2015.

[52] W. Yin, K. Kann, M. Yu, and H. Schütze, "Comparative study of cnn and rnn for natural language processing," *arXiv preprint arXiv:1702.01923*, 2017.

[53] H. Zhang, K. Dana, J. Shi, Z. Zhang, X. Wang, A. Tyagi, and A. Agrawal, "Context encoding for semantic segmentation," in *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, 2018, pp. 7151–7160.

[54] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, "Show and tell: Lessons learned from the 2015 mscoco image captioning challenge," *IEEE transactions on pattern analysis and machine intelligence*, vol. 39, no. 4, pp. 652–663, 2016.

[55] H. Khan, P. M. Shah, M. A. Shah, S. ul Islam, and J. J. Rodrigues, "Cascading handcrafted features and convolutional neural network for iot-enabled brain tumor segmentation," *Computer Communications*, vol. 153, pp. 196–207, 2020.

[56] F. Altaf, S. M. Islam, N. Akhtar, and N. K. Janjua, "Going deep in medical image analysis: concepts, methods, challenges, and future directions," *IEEE Access*, vol. 7, pp. 99 540–99 572, 2019.

[57] E. Tartaglione, C. A. Barbano, C. Berzovini, M. Calandri, and M. Grangetto, "Unveiling covid-19 from chest x-ray with deep learning: a hurdles race with small data," *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, p. 6933, 2020.

PIR MASOOM SHAH holds MS Degree in Computer Science and Machine Learning from the COMSATS University Islamabad, Pakistan. His research interests include medicine, bioinformatics, machine learning, computer vision, ad-hoc networking. He has worked in industry for small startups, large corporations, research labs, as well as been involved in projects sponsored by KP Police. Since September 2019, he has been a Lecturer in Department of Computer Science, Bacha Khan University Charsadda, Pakistan.

FAIZANULLAH is currently pursuing the Ph.D degree in computer science from International Islamic University Islamabad. He is also working as lecturer in Department of Computer Science, Bacha khan university Charsadda, Pakistan. He has published many research articles in reputed journal and conferences. His research interest includes include, Data Mining, Machine learning and Deep Learning.

DILAWAR SHAH was born at District Charsadda, Khyber Pakhtunkhwa (KP) Pakistan. He got his B.Sc. Computer Science degree from historical Islamia College Peshawar and M.Sc. Computer Science from University of Peshawar. He did his MS from the University of Agriculture Peshawar. He started his career as faculty member at Islamia College, Peshawar in 1998. In 2001, joined the University of Agriculture, Peshawar. Mr. Shah joined Abdul Wali Khan University, Mardan KP in 2012. Later on, the campus was upgraded to a fledged University named as Bacha Khan University, Charsadda. Since then he is working as Head of the department at Computer Science Department. His research interest includes medical data mining, social network analysis, text mining and software systems.

ABDULLAH GANI (SENIOR MEMBER, IEEE) received the Teaching Certificate from the Kinta Teaching College, Ipoh, and the Diploma degree in computer science from ITM, the B.Phil. and M.Sc. degree in information management from the University of Hull, U.K., and the Ph.D. degree in computer science from the University of Sheffield, U.K. He is currently a Professor and the Dean Faculty of computing and informatics, University Malaysia Sabah. He is also an Honory Professor with the Department of Computer System and Technology, Faculty of Computer Science and Information Technology, University of Malaya, Malaysia. He obtained tertiary academic qualifications from the University of Hull. He has vast teaching experience due to having worked in a number of educational institutions locally and abroad–schools, Malay Women Teaching College, Melaka, Ministry of Education, the Rotherham College of Technology and Art, Rotherham, U.K., the University of Sheffield, U.K. His interest in research kicked off in 1983 when he was chosen to attend the three-Month Scientific Research Course in RECSAM by the Ministry of Education, Malaysia. Since then, more than 150 academic articles have been published in proceedings and respectable journals internationally within top 10% ranking. He received a very good number of citations in Web of Science as well as Scopus databases. He actively supervises numerous students at all level of study–bachelor's, master's, and Ph.D. area of interest in research include self-organized systems, machine learning, reinforcement learning, and wireless related networks. He worked on mobile cloud computing with the High-Impact Research Grant of USD 800,000 (RM2.5) for the period of 2011–2016. He was also the Principal Investigator of the Research AlQuran and Hadith Authentication Systems with the grant of RM650,000. Besides that, he has received several grants of more than RM350,000. Previously, he was the Director of the Centre for Mobile Cloud Computing Research (C4MCCR), which focuses on high-impact research. The Centre has published more than 60 articles in Tier 1 and Tier 2 ISI-indexed journals. Internationally, he is currently serving as a Visiting Professor with King Saud University, Saudi Arabia, an Adjunct Professor with the COMSATS Institute of Information Technology, Islamabad, Pakistan. He is also serves as a Reviewer to several high-quality journals, and the Chief-in-Editor of the Malaysian Journal of Computer Science and ISI-indexed journal. Locally, he was a Visiting Professor with the University Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia, from 2015 to 2017.

CARSTEN MAPLE is Professor of Cyber Systems Engineering and head of the Secure Cyber Systems Research Group in WMG at the University of Warwick, where he is also the Principal Investigator of the NCSC-EPSRC Academic Centre of Excellence in Cyber Security Research. He is a co-investigator of the PETRAS National Centre of Excellence for IoT Systems Cybersecurity where he leads on Transport & Mobility and Warwick PI on the Autotrust project. He is currently, or has recently been, funded by a range of sponsors, including EPSRC, EU, DSTL, the South Korean Research Agency, and Innovate UK, and private companies. Carsten has an international research reputation and extensive experience of institutional strategy development and interacting with external agencies. He has published over 250 peer-reviewed papers and is co-author of the UK Security Breach Investigations Report 2010, supported by the Serious Organised Crime Agency and the Police Central e-crime Unit. Additionally he has advised executive and non-executive directors of public sector organisations and multibillion pound private organisations. Professor Maple is a fellow of the Alan Turing Institute, a past Chair of the Council of Professors and Heads of Computing in the UK, a member of the Zenzic Strategic Advisory Board, a member of the IoTSF Executive Steering Board, an executive committee member of the EPSRC RAS Network and a member of the UK Computing Research Committee, the ENISA CarSEC expert group, the Interpol Car Cybercrime Expert group and Europol European Cybercrime Centre.

IEEE *Access*

YULIN WANG is a full professor and PhD supervisor in International School of Software, Wuhan University, China. He got PhD degree in 2005 in Queen Mary, University of London, UK. Before that, he has worked in high-tech industry for more than ten years. He has involved many key projects, and hold 8 patents. He got his master and bachelor degree in 1990 and 1987 respectively from Xi-Dian University, and Huazhong University of Science and Technology (HUST), both in China. His research interests include digital rights management, digital watermarking, multimedia and network security, and signal processing. In recently 10 years, Prof. Wang has published as first author 3 books, 40 conference papers and 45 journal papers, including in IEEE Transactions and IEE proceedings and Elsevier Journals. Prof. Wang served as editor-in-chief for International Journal of Advances in Multimedia in 2010. He served as reviewer for many journals, including IEEE Transactions on Image Processing, IEEE Signal Processing Letters, Elsevier Journal of Information Sciences. He served as reviewer for many research funds, including National High Technology Research and Development Program of China (863 project). Prof. Wang was the external PhD adviser of Dublin City University, Ireland during 2008-2010. He was the keynote speakers in many international conferences. He has been listed in Marcus who's who in the world since 2008.

SHAHID Shahid holds MS degree in Computer Science and Machine Learning from Bacha Khan University Charsadda KP, Pakistan. His research interest includes Machine Learning, Bioinformatics, Computer Vision and Data Mining. Mr. Shahid joined the Department of Computer Science, Bacha Khan University as a Lecturer since March 2013 to date.

MOHAMMAD ABRAR received the M.S. degree from The University of Agriculture, Peshawar, Pakistan, in 2008, and the Ph.D. degree from Universiti Teknologi Malaysia in 2017. He is currently serving as an Assistant Professor Bacha Khan University Charsadda, KP, Pakistan. His research interests include bioinformatics, machine learning, and data analysis.

SAIF UL ISLAM received the Ph.D. degree in computer science from the University of Toulouse III Paul Sabatier, France, in 2015. He served as an Assistant Professor with COMSATS University Islamabad (CUI), Pakistan, for three years. He is currently an Assistant Professor with the Department of Computer Science, Institute of Space Technology, Islamabad. He has been part of the European Union-funded research projects during his Ph.D. studies. He was a focal person of a research team at COMSATS University, working in the O2 Project in collaboration with CERN, Switzerland. His research interests include resource and energy management in large-scale distributed systems, such as edge/fog, cloud, and content distribution networks (CDNs), and the Internet of Things (IoT).

• • •