

A Rapid Deep Learning Computer-Aided Diagnosis to Simultaneously Detect and Classify the Novel COVID-19 Pandemic

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Abstract—The novel coronavirus 2019 (COVID-19) becomes recently a global pandemic as declared by the World Health Organization (WHO) in March 2020. COVID-19 rapidly spread and attacked people in more than 200 countries worldwide. The use of artificial intelligence (AI) techniques has become urgent to prevent the exacerbation of the astounding spread of this pernicious disease. This paper presents a novel rapid deep learning computer-aided Diagnosis (CAD) framework for simultaneously detecting and diagnosing the COVID-19 against different respiratory diseases such as pneumonia, atelectasis, cardiomegaly, infiltration, mass, pneumothorax, nodule, and effusion. To develop a useful patient triage system for detecting COVID-19 in early-stage, rapidly extract the visual diagnosis knowledge from the input chest X-ray (CXR) images is extremely required. The proposed CAD framework shows its capability to automatically detect and diagnose COVID-19 with a detection accuracy of 96.31% and a classification accuracy of 97.40%. Meanwhile, the real-time prediction speed of 0.0093 seconds is achieved for a single testing CXR image. To achieve a high accuracy of the knowledge extraction from the entire CXR images with a high prediction speed would represent a key for developing a comprehensive and useful smart patient triage system in hospitals and healthcare systems.

Keywords—COVID-19, Coronavirus2 (SARS-CoV-2), Deep Learning, Computer-aided Diagnosis, Patient Triage System.

I. INTRODUCTION

The respiratory disease of COVID-19 is raised due to the rapid spreading of a novel invisible virus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [1]. This deadly virus is firstly discovered as an obscure respiratory disease in Wuhan city, China. The COVID-19 has rapidly become a global pandemic in around three months since it was firstly discovered at the end of December 2019. At the end of November 2020, world health organization (WHO) reported that the total number of confirmed, death, and recovered cases affected globally by coronavirus have been recorded to be 55.40M, 1.31M, and 38.60M, respectively [2]. Due to the rapidly increasing of the true positive detecting cases of COVID-19, the basic infrastructures of the healthcare system such as beds, ventilators, care providers, and masks are extremely required to support patients and physicians. Indeed, COVID-19 disease has typical clinical symptoms including fever or chills, fatigue, cough, breathing difficulties, muscle and body aches, headache, loss of taste or smell, sore throat, runny nose or congestion, diarrhea, and nausea or vomiting [2, 3]. Globally, WHO announced some precautions for

preventing and minimizing the rapid spreading of COVID-19 such as social distance strategy, wearing medical face masks, washing hands frequently, don not touch eyes, nose, and mouth, disinfecting objects and surfaces frequently, and stay at home. Early and rapidly COVID-19 detection from the input chest X-ray (CXR) images is very important since it has a highly contagious nature, capability to easily spreading, and scarcity of proper vaccine [3]. At present, the real-time reverse transcription-polymerase chain reaction (RT-PCR) tool is a simple screening tool used for COVID-19 detection. Currently, digital radiological imaging modalities of CXR and Computed Tomography (CT) represent the golden screening machines that utilized to detect the COVID-19 lung diseases [1]. Despite the CT examiner is the standard scanning tool, the former CXR machines are still beneficial due to their fine X-ray dose, faster, and more prevalent. However, such imaging scanning routines could be used with the RT-PCR tool to increase the COVID-19 prediction accuracy. The huge number of positive detected cases of COVID-19 makes the regular screening method a daily challenge for physicians, hospitals, and healthcare systems. In the middle of March 2020, the America white house has publicly announced and encouraged expert researchers to apply artificial intelligence (AI) techniques against the crisis of COVID-19 outbreak [4, 5]. Recently, machine learning (ML) and deep learning (DL) approaches have been actively employed to develop CAD frameworks for physicians assisting against COVID-19. Indeed, deep learning applications have been earned a lot of concerns for different medical imaging modalities such as breast cancer [6] and skin cancer [7], etc. The key for using DL techniques is their capabilities to generate huge hierarchical low, middle, and high-level deep features from the entire image [6]. The rapid spreading of COVID-19 raises the necessity to apply such CAD systems to assist physicians and patients as well [4]. This issue has increased our concerns to build a rapid CAD system based on deep learning to diagnose COVID-19. Our presented CAD system should be useful to develop a rapid and smart patient triage workflow based on AI approaches as shown in Fig. 1. The main contribution of this study is to develop a novel rapid CAD-based AI for more accurate diagnosis results and develop a smart patient triage workflow to help physicians, patients, hospitals, and healthcare systems. The presented CAD framework could simultaneously detect and recognize the COVID-19 against all eight respiratory diseases. With pandemic situation as COVID-19, rapid and more accurate clinical decision is required to improve the clinical decision support system (CDSS) for physician as well as medical staff.

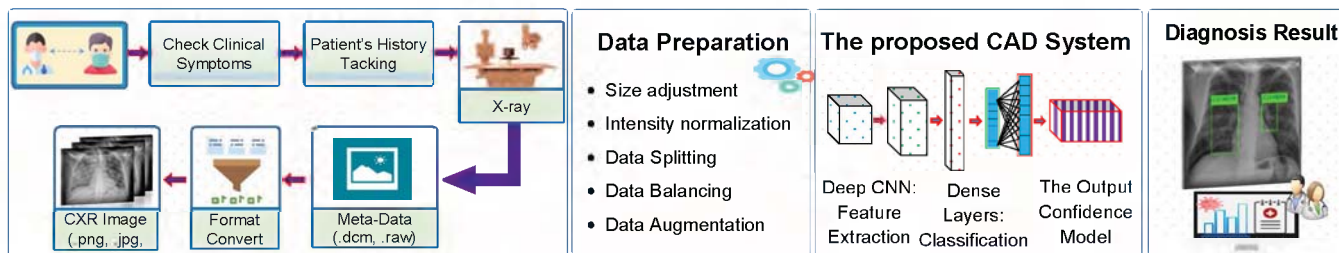


Fig. 1. Schematic diagram of the patient triage workflow using the proposed deep learning CAD system based on the YOLO predictor.

II. RELATED WORKS

After disclosing the novel COVID-19 pandemic, few studies based on artificial intelligence (AI) approaches have been proposed to reveal the COVID-19 from digital CXR or CT. In [1], Oh et al. presented a patch-based deep learning CAD system consisting of segmentation and classification stages to recognize the COVID-19 from the CXR images. They achieved diagnostic performances of 84.40% and 88.90% in terms of F1-score and overall accuracy, respectively. Ozturk et al. [8] presented a DarkCovidNet DL model to recognise the COVID-19 using the whole CXR images. By using 17 convolutional layers their model is developed for binary task (Normal vs. COVID-19) and multi-class task (Pneumonia vs. Normal vs. COVID-19). For the binary and multi-class reorganization tasks, their proposed DL model achieved overall diagnostic accuracies of 98.08% and 87.02%, respectively. In [9], Wang et al. proposed a DL COVID-Net to classify COVID-19 against normal and pneumonia lung diseases from CXR images. Their presented model outperformed ResNet-50 and VGG-16 achieving positive predictive values (PPV) of 98.9%, 90.50%, and 91.30% for COVID-19, normal, and pneumonia cases, respectively. In [10], Ardakani et al. presented the evaluation study using ten different well-established DL models to diagnose COVID-19 in routine clinical practice using CT images. They diagnosed COVID-19 against Non-COVID-19 in a binary classification task and they achieved the best diagnosis result using ResNet-101 and Xception DL networks with overall accuracy of 99.40% for each. In [5], Apostolopoulos et al. used five well-established deep learning networks for detecting the pandemic of COVID-19 from CXR images. They tested all these DL models for the binary (i.e., COVID-19 vs. normal) and multi-class recognition tasks (i.e., pneumonia, COVID-19, and normal). They concluded that the highest overall diagnostic accuracies of 93.48% and 98.75% are achieved via VGG-19 for binary and multi-class recognition tasks, respectively. Moreover, comprehensive survey studies on the DL applications to fight COVID-19 are presented in [11, 12]. However, such presented DL models are tested for diagnosing COVID-19 pandemic using the whole CXR images. The whole CXR image always involves irrelevant or mixture textural structure details that make the derived deep features are not feasible enough to represent a specific respiratory disease. In fact, the diagnosis of knowledge extraction using the whole CXR image may not provide a superior practical solution for a more feasible diagnostic performance of any CAD system. Thus, the extraction of the specific regions or patches from the whole CXR images involving only the lung diseases (i.e., COVID-19 or another disease) to train DL models is a key to improve the overall diagnosis performance. In our knowledge, this is the first regional ROI based on DL CAD system proposed to automatically reveal and distinguish the COVID-19 pandemic from the whole input CXR images in a multi-class recognition problem.

III. MATERIAL AND METHODS

A. Data Set

For training and validating purpose, two CXR databases are used: COVID-19 and ChestX-ray8. All CXR images from these databases are publically available. For COVID-19 database, we use 326 CXR images that collected from two different sources as follows. First, CXR COVID-19 images generated by Cohen et al. from different public hospitals and radiologists are used. This sub-dataset consists of 125 images from positive COVID-19 patients. Second, we use 201 CXR images from positive COVID-19 patients. These images are collected by the research team at Qatar university with a fixed size of 1024×1024 pixels as a '.png' file format. The information of the ground-truth (GT) localization (i.e., bounding box coordinates) for the images in the COVID-19 dataset are determined by experts. For ChestX-ray8 database, we utilize all annotated CXR images (i.e., 984 CXR images) from eight different respiratory diseases: atelectasis, infiltration, pneumothorax, mass, effusion, pneumonia, cardiomegaly, and nodule. All X-ray images in this database are converted from DICOM into '.png' file format and resized into a fixed size of 1024×1024 pixels.

B. Data Preparation

The input CXR images are scaled and normalized via bi-linear interpolation into a fixed size of 448×448 pixels to reduce the dimensionality of the input images, minimize the number of trainable parameters, and accelerate the training process [13]. For each specific class, CXR images are randomly split into 70%, 10%, and 20% for training, validation, and evaluation, respectively. After that, balancing and augmentation methodologies are used to tackle the scarcity of the medical dataset, enlarge the training dataset size, prevent the overfitting, and accelerate the training process [7]. For dataset balancing, all CXR images collected from the ChestX-ray8 database are flipped up-down and left-right to produce 1,378 CXR images. That is to match the majority images of the COVID-19. After balancing, the generated training dataset became 2,295 CXR images (i.e., 917 original images + 1,378 balanced images). By applying the augmentation strategy, the size of the training dataset is increased 22 times as follows. First, the original images are translated and scaled 10 times. Second, all images are also rotated by 0° , 45° , 90° , 135° , 180° , 225° , 270° , and 315° . Finally, rotated images with angle of 0° and 270° are flipped twice. In a total, 50,490 images are generated for the training purpose.

C. Deep Learning Structure of the Proposed CAD System

For simultaneous detecting and classifying of the COVID-19 and other diseases, a regressor deep learning model of CAD-based YOLO predictor is adopted and used [6]. This CAD system is developed as a unique DL architecture that could simultaneously optimize trainable parameters (i.e., weights and biases) end-to-end for both detection and classification

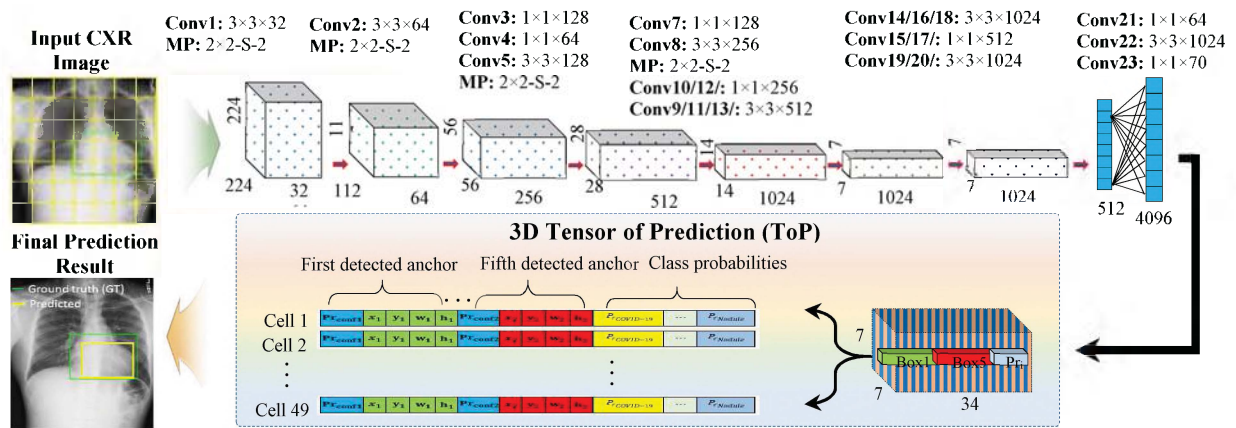


Fig. 2. The detailed components of the proposed CAD system via deep learning YOLO predictor.

tasks as shown in Fig. 2. Batch normalization and reduction layers are added after convolutional layers to accelerate the convergence, diminish the overfitting, and stabilize the training process [14]. In addition, 2×2 max-pooling (MP) is applied 5 times. At the last convolutional layer, cumulated deep feature maps are flatted and then concatenated utilizing the global average pooling [6]. Then, they immediately fed into the dense layers to predict the anchors' coordinates and their class labels. Indeed, the presented CAD divides the whole input image into $N \times N$ patches. If the object center exists in the specific patch, then, that patch should be responsible to reveal that object. For each patch, five anchors are used for object prediction. For each anchor, the YOLO detects 5 predictors: center (x, y), width (w), height (h), and confidence score probability ($Pr_{conf.}$). For training, the estimated confidence value for each anchor is defined as,

$$\text{Confidence} (Pr_{conf.}) = \text{Prob}(\text{object}) \times \text{IoU}_{\text{Pred.}}^{\text{GT}}. \quad (1)$$

where $\text{Prob}(\text{object})$ and $\text{IoU}_{\text{Pred.}}^{\text{GT}}$ represent the probability of the disease and the value of the intersection over union (IoU). Based on both object probability and $\text{IoU}_{\text{Pred.}}^{\text{GT}}$, the coordinates of detected anchors are optimized to tight the object that may fall in the specific patch. In each patch, the conditional class probabilities for all 9 classes are predicted. The confidence scores of the predicted anchors are estimated as follows,

$$\text{Confidence Score} = \text{Prob}(\text{Class}_i | \text{object}) \times \text{Confidence}; i = 1, 2, 3, \dots, \text{and } 9 \quad (2)$$

where i is the number of classes and the $\text{Prob}(\text{Class}_i | \text{Object})$ is

$$\text{Prob}(\text{Class}_i | \text{Object}) = \frac{\text{Prob}(\text{Class}_i)}{\text{Prob}(\text{Object})} \quad (3)$$

Then,

$$\text{Confidence Score} = \text{Prob}(\text{Class}_i) \times \text{IoU}_{\text{Pred.}}^{\text{GT}}. \quad (4)$$

At the prediction phase, to estimate the confidence score for each anchor, where the GT information is not available, the individual box confidence value is multiplied by the conditional class probability of that box [6]. The detected box with highest confidence value represents that the object of COVID-19 or another lung disease is existed and it represents the final output. Each box has confidence score as,

$$\text{ConfidenceScore}_{\text{box}_i} = \text{argmax} \left\{ \left(Pr_{\text{conf.}_i} \times \text{Pr}(\text{class}_i | \text{object}) \right), \left(Pr_{\text{conf.}_{i+1}} \times \text{Pr}(\text{class}_{i+1} | \text{object}) \right), \dots \right\}; i = 1, 2, 3, \dots, \text{and } 9. \quad (5)$$

The final detected box with the heights confidence probability represents the final detected output of the CAD system. Other detected anchors having $\text{IoU}_{\text{Pred.}}^{\text{GT}} < 45\%$ with lower confidence scores are ignored by using non-max suppression (NMS) algorithm. As shown in Fig. 2, each patch in the input

image is represented in the ToP by coordinates of the 5 anchors (x, y, w , and h), confidence scores ($Pr_{conf.}$), and conditional class probabilities of all 9 classes of lung diseases. The size of the ToP is determined by 3D matrix of $N \times N \times (5 \times B + C)$ where N , B , and C are the number of patches, boxes, and classes. $N=7$ and $B=5$ are used in this study. This means the output dense layer has 1,666 neurons [13].

D. Experimental Setting

The proposed DL model uses the multi-scale training strategy to randomly resize the input CXR image resolution for learning purpose with different image resolutions [3]. Mmini-batch size and number of epochs of 24 and 120 are utilized for training/validating purpose, respectively. A specific PC is used to execute this study: Intel® Core (TM) i7-6850k, speed of 3.36 GHz, 16 GB RAM, and 4 GPUs.

E. Experimental Evaluation Strategy

There are two specific conditions to detect the final region of interest (ROIs) of the suspicious respiratory disease [3]. First, $\text{IoU}_{\text{Pred.}}^{\text{GT}}$ between the predicted and its GT must be $\geq 45\%$. Second, the final detected box should have the confidence score (i.e., Pr_{conf}) equal or greater than 10%. These proper threshold values are experimentally determined. For quantitative evaluation, we utilize the weighted objective indices as mentioned in our published paper [13]. To prevent the unbalancing testing datasets for all 9 classes, the weighted class strategy is used [13].

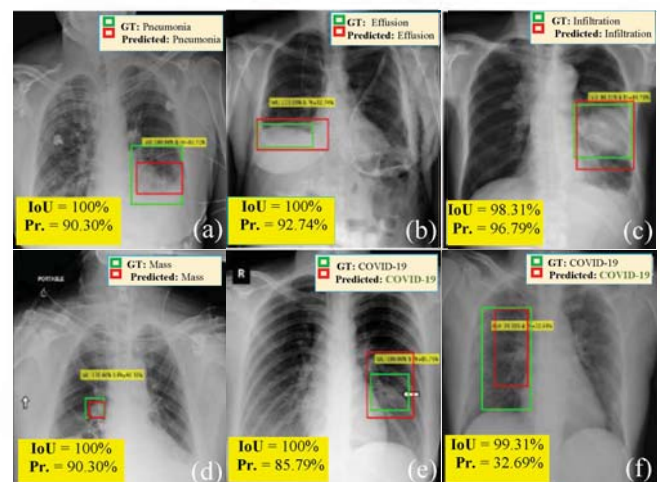


Fig. 3. Examples of the qualitative results of the true predicted COVID-19 and other respiratory diseases. The GT (green) and their predicted anchors (red) are superimposed on the original images.

IV. RESULTS AND DISCUSSION

A. Experimental Detection Results

Our CAD system show its capability for detecting the suspicious regions of COVI-19 or another lung disease as shown in Fig. 3. The detected ROIs are assigned as correctly revealed if and only if their $IoU_{Pred}^{GT} \geq 45\%$ and $Pr_{conf.} \geq 10\%$. As an average of the five-folds, the proposed CAD system could detect COVID-19 with overall detection accuracy of 96.31% as reported in TABLE I.

TABLE I. DETECTION RESULTS OVER 5-FOLDS FOR THE TESTING DATASET

Class	Detection Evaluation Results per Class (%)	
	True Detection	False Detection
COVID-19	96.31	3.69
Atelectasis	88.89	11.11
Infiltration	97.60	2.40
Pneumothorax	71.50	28.50
Mass	90.59	9.41
Effusion	91.61	8.39
Pneumonia	86.67	13.33
Cardiomegaly	97.24	2.76
Nodule	78.75	21.25

B. Experimental Classification Results

The proposed CAD predictor could simultaneously recognize the extracted regions of COVID-19 and all other diseases. As depicted in Fig. 3, our CAD system could detect the suspicious patches of respiratory diseases and recognize them concurrently. This is the crucial point making the proposed CAD system much faster with high accurate diagnosis results. The classification results are computed based on the multi-class contingency tables for all 9 classes in each fold. Moreover, weighted classification evaluation metrics over 5-folds are reported in TABLE II. It is obviously noticed that the CAD system could achieve average classification accuracies in the range of 94.6% and 97.4% for pneumonia and COVID-19, respectively. The presented CAD system seems to achieve a promising diagnostic performance of different respiratory diseases. Moreover, the regularization strategies of data balancing and augmentation are clearly boosted CAD system for more classification improvements. Thus, the average classification performance per class is improved in terms of SE, SP, ACC, Dice, MCC, PPV, and NPV by 12.91%, 4.49%, 6.64%, 12.17%, 12.99%, 11.72%, and 3.56%, respectively. For testing time, the proposed CAD system predicts an individual image in 0.0093 seconds. Thus, the proposed CAD system has reliability to predict 108 frame/sec in real-time.

TABLE II. CLASSIFICATION EVALUATION RESULTS (%) OVER 5-FOLD TESTS

Folds	SE	SP	ACC	Dice	MCC	PPV	NPV
fold1	88.25	99.16	97.59	85.47	83.6	86	98.91
fold2	84.5	99.1	97.37	84.76	82.76	85.32	98.71
fold3	83.32	98.77	97.08	83.62	81.51	84.41	98.69
fold4	85.26	99.15	97.59	85.48	83.61	86.1	98.92
fold5	84.5	99.1	97.37	84.76	82.76	85.32	98.71
Avg.	85.17	99.06	97.40	84.82	82.85	85.43	98.79

V. CONCLUSION

In this paper, a novel regional DL CAD framework is presented to simultaneously predict the COVID-19 from CXR images. The CAD system is developed as a unique DL structure to rapidly reveal the abnormalities patches of COVID-19 or other respiratory diseases from the whole CXR images. Our CAD framework achieves much satisfactory diagnosis accuracy of 97.40% for a multi-class classification task. The rapid prediction time with high accuracy performance makes the presented CAD system a reliable solution to assist physicians, patients, hospitals, and health care systems.

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