Coronavirus disease 2019 detection using deep features learning

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ABSTRACT

A Coronavirus disease 2019 (COVID-19) pandemic detection considers a critical and challenging task for the medical practitioner. The coronavirus disease spread so rapidly between people and infected more than one hundred and seventy million people worldwide. For this reason, it is necessary to detect infected people with coronavirus and take action to prevent virus spread. In this study, a COVID-19 classification methodology was adopted to detect infected people using computed tomography (CT) images. Deep learning was applied to recognize COVID-19 infected cases for different patients by employing deep features. This methodology can be beneficial for medical practitioners to diagnose infected patients. The results were based on a new data collection named BasrahDataset that includes different CT scan videos for Iraqi patients. The proposed system gave promised results with a 99% F1-score for detecting COVID-19.

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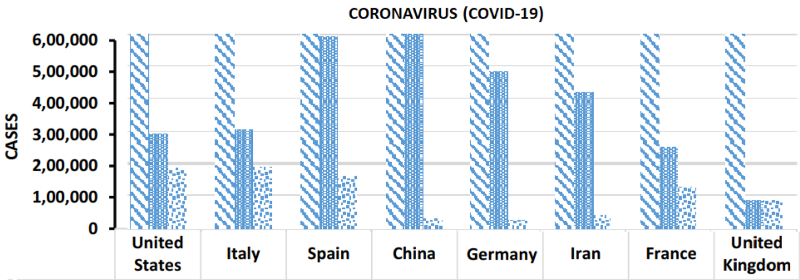
1. INTRODUCTION

In December 2019, a novel coronavirus called 2019-nCoV ("n" stands for a novel) spread. This virus causes severe acute respiratory (SARI) symptoms, including dyspnea, fever, asthenia as well as pneumonia. The virus spread among Chinese people (specifically in Wuhan). The first batch of Chinese infected people is all roughly associated with the seafood market in Wuhan that also trades wild animals. Then, contact transmission of 2019-nCoV was confirmed among humans and the number of infected Chinese people increased rapidly not only in Wuhan but also in other major cities in China. Many actions have been taken by the Chinese government to avoid and control the pandemic, but the coronavirus spread rapidly outside China and moves out to the world. Like any place in the world, many COVID-19 positive cases appeared in Iraq. The number of individuals that contracted the virus increased sharply and continues to evolve rapidly. On 23 June, the positive cases reaching 34,502 patients were associated with a significant increase in the number of deaths. Roughly 40% of these cases were identified in Baghdad [1]–[5]. Figure 1 shows the number of recovered and death COVID-19 cases [6]. Figure 2 shows the number of death cases in Iraq [7].

The diagnosis of coronavirus (COVID-19) nowadays is a critical task for the medical practitioner, especially with an increased number of patients and a variety of symptoms. The test of COVID-19 in Iraq is currently a difficult task due to the unavailability of the diagnosis system in every city, which is causing delays in disease detection. Due to the limited supply of COVID-19 testing kits, other diagnosis measures are needed to rely on. Since COVID-19 attacks the epithelial cells that line our respiratory tract, we can use computed tomography (CT) scan images to analyze the health of a patient's lungs and since CT images are used frequently to diagnose lung inflammation, pneumonia, abscesses, and/or enlarged lymph nodes and nearly all hospitals have CT imaging machines, these machines are used to test COVID-19 suspected cases instead of dedicated test kits. The main problem of using CT image is that the analysis of CT images requires a radiology expert, and it takes a long time to have a diagnosis which is a luxury that sick people don't have. Therefore, it is necessary to develop an automatic system capable of analyzing the CT images to save time and have faster diagnosis [8]–[11].



	United States	Italy	Spain	China	Germany	Iran	France	United Kingdom
Confirmed	5,05,015	1,47,577	1,61,852	81,953	1,22,627	70,029	90,676	73,758
Recovered	29,107	30,445	59,109	77,525	48,692	41,947	24,932	9,000
Deaths	18,771	18,849	16,353	3,339	2,710	4,357	13,197	8,958

Figure 1. Statistics of COVID-19 in some countries

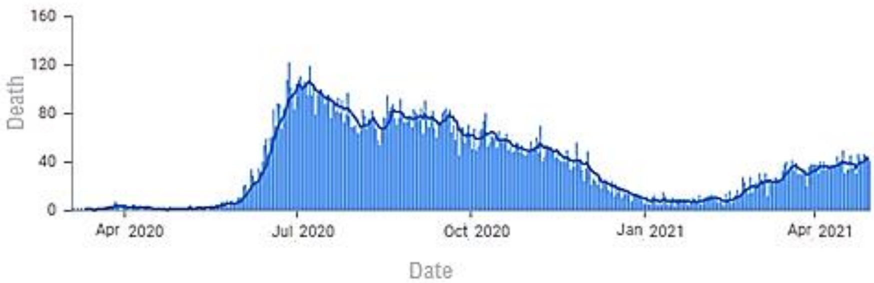


Figure 2. Number of COVID-19 death cases in Iraq

During the current corona pandemic, many classification systems based on machine learning (ML) and deep learning (DL) presented grand proof of success in the scope of understanding medical images due to their high classification and feature extraction capabilities [8]. For example, Li *et al.* [12] used two CT lung images, uCT and uMI scanners (United Imaging), to examine the relationship between the manifestations of CT imaging and the clinical categorization of COVID-19. They conducted a retrospective single-center study on 78 patients (38 males and 40 females) with COVID-19 from 18 January 2020 to 7 February 2020 in Zhuhai city, China that divided the patients into three types based on Chinese guidelines. The first type is mild included patients with negative CT image findings and minimal symptoms. The second type is common, and the third one is severe-critical included patients with different extent of clinical manifestations and positive CT image findings. They used different scores to CT visual quantitative estimation based on summing up the acute lung inflammatory lesions comprising each lobe. The total severity score (TSS) was compared with the clinical classification. The cutoff point of TCC is 7.5 that yielded 82.6% sensitivity and 100% specificity. They concluded that the ratio of COVID-19 patients of mild-type was comparatively high; CT images were not appropriate as an independent screening tool. The visual quantitative analysis of CT image has high consistency and consequently can reflect the clinical categorization of COVID-19.

Narin *et al.* [13] used three different convolutional neural net (CNN)-based models (ResNet50, InceptionV3, and Inception- ResNetV2) to detect infected people with coronavirus pneumonia and utilized chest X-ray radiographs. They used ResNet50 to pre-trained the model. The classification accuracies were

98%, 97% and 87% for ResNet50, InceptionV3 and Inception-ResNetV2 respectively. The experimental result was based on using a 100 chest X-ray images dataset (50 images of normal cases, and 50 COVID-19 patients). The authors concluded that using COVID-19 automatic detection can help doctors to detect coronavirus at an early stage, and consequently appropriate decisions can be taken based on the high performance of the classification model. Barstugan *et al.* [14] used different CT tools to extract the coronavirus image set. These images dataset was collected manually included 150 CT abdominal images that belong to 53 infected cases from the Societa Italiana di Radiologia Medica e Interventistica. To extract image features, five feature extraction approaches (grey level co-occurrence matrix, grey level size zone matrix, grey level run length matrix, local directional pattern, and discrete wavelet transform) were utilized to exclude the irrelevant feature set. The classification accuracy achieved was 99.68%.

Behera and Kumari [15] used deep learning for the detection of coronavirus infected people utilized X-ray images. The features extracted from the deep feature of nine pre-trained CNN models and passed to the support vector machine (SVM) classifier model individually. Two datasets utilized in this study, the first dataset included 25 positive cases and 25 negative cases that were collected from the GitHub repository shared by Cohen [16] and Kaggle repository [17]. While the second dataset included 266 (133 positive cases and 133 negative cases) that were collected from the open-i repository [18]. The classifier system achieved 95.52%, 95.38% of F-Score, and accuracy respectively, for detecting COVID-19 disease (ignoring acute respiratory distress syndrome (ARDS), Middle East respiratory syndrome (MERS), and severe acute respiratory syndrome (SARS)). Song *et al.* [19] collected 275 CT scan images from two hospitals in China distributed to 88 positive COVID-19 cases, 101 images for patients infected with bacteria pneumonia, and 86 images for healthy persons. They used four deep learning models (VGG-16, DRENet, ResNet, and DRE-Net) for Pneumonia classification. The best f-score result was 87% in the test set. Abdulmunem *et al.* [20] also used COVID-19 X-ray images of the Kaggle dataset to train the ResNet50 deep learning network. The best results were obtained with 5 folds cross-validation with an accuracy rate of 97.28%. In the work of [8], deep learning network modification was used to detect Covid-19 positive cases by extracting features from CT images and chest X-rays. Two essential phases were adopted. In the first one, many transfer-learning models were applied, while the second phase used a VGG-19 model to find the best results for disease diagnosis. 1,000 images were used for evaluation VGG-19 model that achieved 99% of accuracy, 97.4% of sensitivity, and 99.4% of specificity.

The contribution of this paper is to develop an automated diagnostic system using VGG-16 capable of analyzing the COVID-19 either positive or negative cases from radiology images and consequently obtaining a rapid and accurate diagnosis. The remaining sections of this paper are structured as the following: Materials and methods will be shown in section 2. In section 3, the experimental results and discussions will be detailed. Finally, the conclusions are shown in section 4.

2. MATERIALS AND METHODS

2.1. VGG-16 model

Simonyan *et al.* [21] proposed VGG-16 architecture as a CNN model. They used this model to win ILSVR (ILSVRC (Imagenet large scale visual recognition challenge)) competition in 2014. VGG-16 consists of sixteen-layer network and is considered one of the best vision model frameworks to date. VGG-16 model yielded 92.7% top-5 test accuracy in ImageNet dataset that included over fourteen million images distributed into 1,000 classes. To train VGG-16, many weeks were required. As shown in Figure 3, the VGG-16 structure of the layers can be summarized as follows: First and second layers: The input image is 224×224×3 passed through a stack of first and second convolutional layers with 64 feature maps or 3×3 filters and stride 14 for the same pooling. The dimensions of the images will be changed to 224×224×64. Then, the maximum pooling layer or layer of sub-sampling will be applied in the VGG-16 with a filter size 3×3 and stride 2. The dimensions of the resulting image will be minimized to 112×112×64. Third and fourth layer: After that, two convolutional layers are applied with 128 feature maps having filtering size 3×3 with a stride of 1. Next, a maxpooling layer with filter size 3×3 with a stride of 2 is implemented, which consequently reduces the dimension of the resulting image to 56×56×128. Fifth and sixth layers: These two layers are convolutional layers having filter size 3×3 with a stride of one. Both layers utilized 256 feature maps. The next layer of these convolutional layers is the layer of maximum pooling having filter size 3×3 with a stride of two and 256 feature maps. Seventh to twelfth layer: These convolutional layers that followed by a maximum pooling layer having 512 filters of size 3×3 with a stride of one. The final dimension will be decreased to 7×7×512. Thirteenth layer: the fully connected (FC) layers are used to flatten the convolutional layer output with 25,088 feature maps each of size 1×1. Fourteenth and fifteenth layers: These layers consist of two fully connected layers with 4096 units. Output layer: The final layer is the SoftMax output layer with 1,000 classes [22], [23].

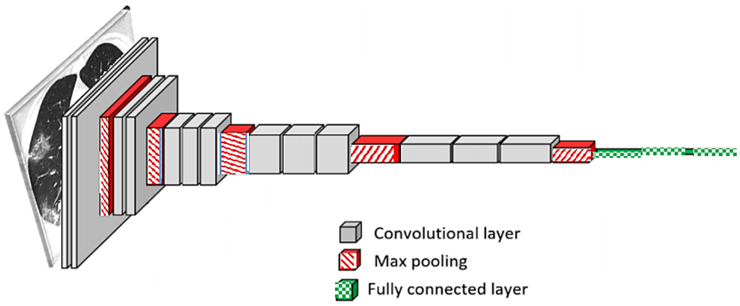


Figure 3. VGG-16 neural network architecture

2.2. Proposed method

Image classification is the process of automatically assigning a class label to the new images based on pre-defined patterns created from labeled data. The classification system divides the data into training and testing phases. During the training phase, optimal parameters are obtained and used in the testing phase to predict the label to the new images. The adopted classification system consists of four main phases as shown in Figure 4: pre-processing stage, deep CNN feature extraction phase, classification phase, and evaluation phase. Processing is an important stage used to prepare the images for the next phase. Next, feature extraction is applied to extract the features and excluding the unimportant features using deep learning filtering. Then, the extracted features will be passed to the classifiers to find the best results. Finally, the evaluation is applied to compute the classifier performance. In the following subsections, these phases are explained.

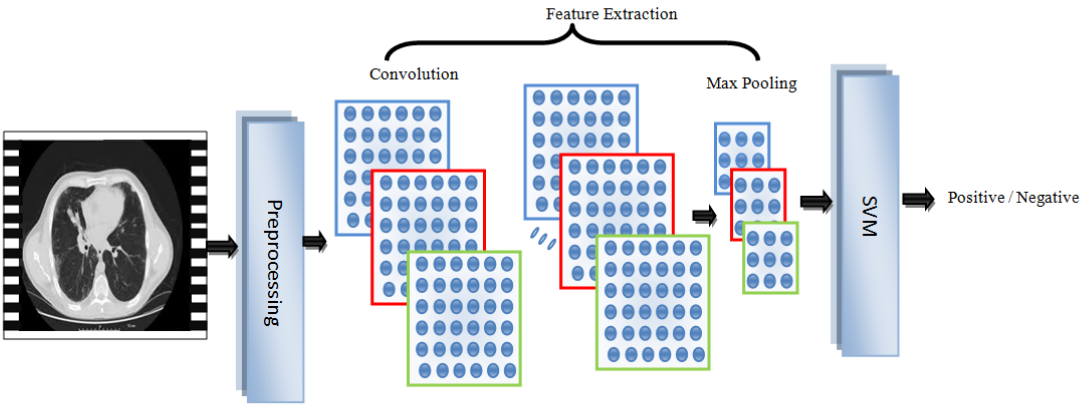


Figure 4. The adopted classification system

2.2.1. Basrah dataset

The data used in the current study collected from Al-Sadr educational hospital in Basrah, Iraq. These video data were collected manually for Iraqi patients in Basrah City and called (BasrahDataset) by a specialist in Infectious diseases during the period from April to June 2020 and included the chest X-ray (CXT), and computed tomography (CT) scan images. BasrahDataset includes 50 cases distributed into 30 males and 20 females with two positive and negative COVID-19 cases. The age of the patients ranged between 18 and 65. The total images are roughly 1,423 (1,181 positive cases, and 242 negative cases). These data are confirmed by a clinical picture in addition to polymerase chain reaction test (PCR). The use of this data in the current study is based on the official approval document issued by the Al-Sadr educational hospital. The automatic detection system is built based on the above expert experience by dividing the data into two groups: training and testing. Training data comprised approximately 818 images with 694 images confirmed COVID-19 cases. While 124 images are negative cases. On the other hand, 487, and 118 positive and negative cases are used for testing (605 images in total) respectively. Figure 5 shows an example of BasrahDataset CT images. The first one is used to learn the extracted deep feature to build the classifier model using VGG-16 and another one is to identify the COVID-19 infected patient automatically by using this built model. Keras package in python language (version 3.7.4 64-bit) used to design VGG Model.

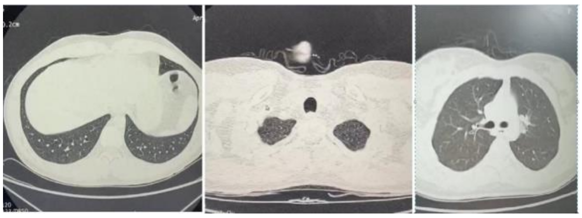


Figure 5. An Example of CT Images

2.2.2. Preprocessing phase

Preprocessing is an important stage used to prepare the image for the next step. Preprocessing is a set of processes that applied to the image to exclude the noise and extract the region of interest (ROI). In the first step, the CT image is transformed into the grayscale and resizes the images. All the images in the dataset will be passed as input to the VGG-16 neural networks model of the same size. So, all images need to be resized into a fixed size with less shrinking to avoid classification accuracy degradation due to deformations. In addition to that, the amount of the required memory and computational operations for image processing also reduced [24], [25].

2.2.3. Deep CNN features extraction

A deep CNN framework is composed of different layers used as a feature extractor. Earlier CNN layers have more low-level features compared with the highest level (convolution layer or pooling layer). The CNN hidden layers consist of one or more convolutional layers each follow up by a pooling layer in a sequential manner and follow up by one or more fully connected (FC) layers. The CNN convolutional layers are used to extract the relevant features, while the last FC layer is used as a classifier. The convolutional layers comprised form two different layers: the filter bank layer as well as the nonlinearity layer. The features are mapped as a matrix and passed as input to the convolutional layers. The matrix dimensions are W×H×3, where W and H are the width and height respectively, and 3 (three-color channeled RGB image) is the number of feature maps. The layers of the filter bank include multiple trainable kernels associated with each feature map. Each kernel capable of identifies a specific feature from the input matrix at every location. on the other hand, the nonlinearity layer implements on the output a nonlinear activation function from the filter bank layer. After that, the pooling layers are applied to sub-sampling for each feature map in order to decrease the map resolution. Then, the output of the convolutional layers is passed to FC layers. During FC layers, the final decisions based on different weighted combinations of the inputs are making to determine the class that the image belongs to [25].

2.2.3. Classification phase

In this phase, the classification process is discussed. Essentially, it is required to have two main combined steps in to classify images obtained by CT scan. Those images will be utilized to recognize the infected patients with COVID-19. Firstly, deep features that are extracted from the CNN model based on the CT scan images will be the inputs data to a support vector machine classifier with a linear-kernel function. Secondly, the trained classifier is applied to the test images by feeding the features obtained from the previous layers to the SVM classifier. This in turn will lead to identify COVID-19 infections which will be either positive or negative.

2.2.4. Evaluation phase

The performance of the classification can be evaluated by using precision, recall, and F1-score. The classification system performance was measured with the F1-score and the Accuracy calculated by the following formula [26]–[28]:

$$Accuracy\ =\ (TP+TN)(TP+FP+TN+FN) \tag{1}$$

$$F-score=(2\times Recall\times Precision)/(Recall+Precision) \tag{2}$$

where true positive (TP) indicates the number of correctly cases that recognized for the class, False positive (FP) indicates the number of correctly recognized cases which do not belong to the class. True negative (TN) indicates the number of cases that were incorrectly assigned to the class, and false negative (FN) is the cases that were not recognized as class cases. Precision is the number of correctly classified positive cases that can be divided by the number of cases labeled by the system as positive.

$$Precision = TP/(TP + FP) \tag{3}$$

And recall (Sensitivity) is the number of correctly classified positive cases divided by the number of positive cases in the data. Specificity is a measure of how well the program distinguishes the case of patients that do not have the COVID-19 disease.

$$Recall = TP/(TP + FN) \tag{4}$$

$$Specificity = TP/(FP + TN) \tag{5}$$

3. RESULTS AND DISCUSSION

The convolutional neural network (CNN) architecture is executed with many layers such as convolutional, rectified linear unit (ReLU), and pooling. The ReLU activation function is used in hidden layers and SoftMax is used in the output layer. Also, average and fully connected layers are used. Further layers are used like dropout that added to the network to improve the classifier performance during the training phase. This layer is activated only in the training phase to drops a certain number of neurons randomly during the forward pass. The non-dropped neurons are updated during the backward pass. The main purpose of dropout is to bring the regularization to learn the model with a robust feature and avoids overfitting during the training phase. The input CT images are passed into the CNN detection pipelines that started with deep feature extraction and ended with making decisions. The detection performance in the current study is evaluated utilized the VGG-16 pipeline CNN based on the loss-accuracy curves to obtain the best class. The BasrahDataset is used for evaluation. The total images are roughly 1,423 that are divided into two groups: training, and testing. Roughly 818 CT images were used for training and validation (654 images for training and 164 for validation). Then, 605 CT images are used to evaluate the pre-trained model. Figure 6 shows the experimental results with the best accuracy and loss. The right prediction rate of a dataset of trained or validated images is represented by a point in the accuracy curve. It can be noted that the accuracy of the training dataset is around 100% after 10 epochs as well as the validation set accuracy. The test accuracy of BasrahDataset testing images is 99%.

VGG-16 achieved the highest sensitivity of 99%. Similarly, the specificity indicates the true negative rate. Besides, the adopted classification system achieved better results compared to the related works in terms of data type, data size, and used classifier. Table 1 shows other researchers' work using different deep learning techniques and datasets for the prediction of COVID-19. The advantage of our work is using a large number of the dataset with high accuracy.

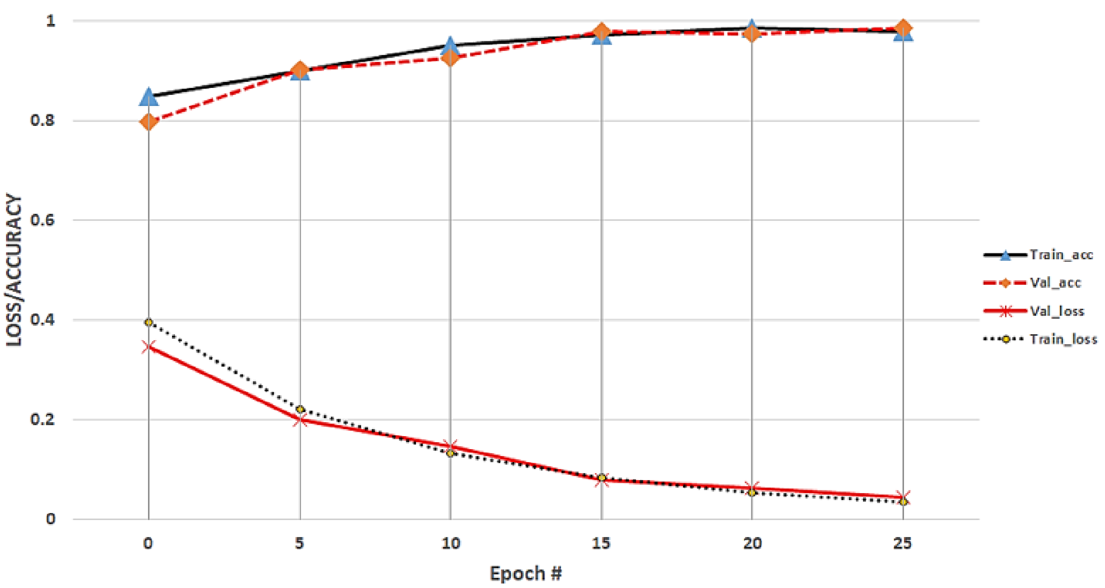


Figure 6. Loss and accuracy on basrahdataset

Table 1. Comparisons between our proposed system and some related works

Reference	Classifier	Type of data	Amount of data	Classifier performance
Kamil [8]	VGG-19	CT images and chest X-ray	1,000 images	99% accuracy
Li *et al.* [12]	Statistical analysis	CT chest images	1,540 images	82.6% Sensitivity, 100% Specificity
Narin *et al.* [13]	CNN	Chest X-ray images	100 images	98% Accuracy
Barstugan *et al.* [14]	SVM	CT Chest images	150 images	99% Accuracy
Sethy *et al.* [15]	CNN	Chest X-ray images	316 images	95.52% F-score, 95.38% Accuracy
Song *et al.* [19]	VGG-16	CT Chest images	275 images	84% F-score and Accuracy
Abdulmunem *et al.* [20]	ResNet50	Chest X-ray images	50 images	97.28% accuracy
Current Study	VGG-16	CT Chest images	1,423 images	99% F-score and Accuracy

The main contributions of the current study can be summarized in few points which are: the proposed system does not suffer from data imbalance, the utilized VGG-16 model was trained with a large number of CT scan images of COVID-19 compared to the previous studies. Besides the proposed system is fully automated diagnosis system that did not need anyprior operation to extract features. Even though the above-mentioned advantages, there are some limitations in the proposed system such as the current system needs training different types of respiratory diseases, this considers as future work to improve our system. Therefore, the current system is only diagnosed COVID-19 infected people compared with healthy individuals and it is unable to diagnose other types of pneumonia and respiratory diseases.

4. CONCLUSION

In this paper, deep classification learning is adopted to identify COVID-19 CT images. These images collected from Iraqi patients in Basrah city consisted of 1,423 CT images for positive and negative COVID-19 cases. The classification model extracts the features from the pre-trained dataset. Then, the SVM classifier was used to recognize the coronavirus cases. The classification system achieved relatively high performance on BasrahDataset CT images. Besides that, results were also compared with some related works in future work, we can develop the system to diagnose some other respiratory disease, also to detect the level of coronavirus infection.

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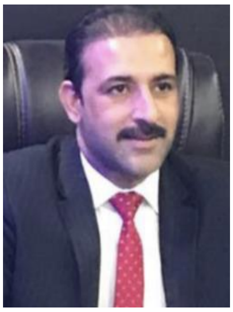

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