Automatic COVID-19 Diagnostic and Classification Intelligent System (ACDCIS)

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Mohammed Faisal Naji
Center of AI & Robotics, Kuwait
College of Science and Technology (KCST), Kuwait
m.naji@kcst.edu.kw

Fahad Alzamil
College of Applied Computer Sciences
King Saud University, Saudi Arabia

Mohammed Alajaj
College of Applied Computer Sciences
King Saud University, Saudi Arabia

Musaad Alshaqran
College of Applied Computer Sciences
King Saud University, Saudi Arabia

Fahad Alateeq
College of Applied Computer Sciences
King Saud University, Saudi Arabia

***Abstract*—Coronaviruses are a huge gathering of infections that can contaminate both creatures and people. An assortment of coronaviruses is known to cause respiratory infections in people, extending from the common cold to more extraordinary sicknesses such as the Center East Respiratory Disorder (MERS) and extraordinary intense respiratory disorder (SARS). COVID-19 is caused by a recently distinguished coronavirus. Recognizing and diagnosing these cases of respiratory infections and the COVID-19 infection has been troublesome for health associations. Therefore, in this research, we will develop an Automatic COVID-19 Diagnostic and Classification Intelligent System (ACDCIS) based on Machine Learning (ML). The proposed ACDCIS consists of two sub-systems the three-classifier system and two-classifier system. The two-classifier system is used to determine if the patient has a Covid-19 or not, while the three-classifier system is used to specify the type of infection COVID-19, bacterial infection, or virus pneumonia infection. The high accuracy of the proposed ACDCIS system will increase the speed of diagnosis.**

Keywords—Covid-19, ResNet50, vgg-19. Machine learning

I. INTRODUCTION

On December 31, 2019, COVID-19 started with the announcement of pneumonia caused by unknown causes in Wuhan, China, and quickly spread into a pandemic, COVID-19 is the title of the illness. In fair 30 days, the new infection spread from Wuhan to most of China, At that point, it spread to the United State, with the primary seven cases recorded on January 20, 2020, and after that to the rest of the world. SARS is a severe form of acute respiratory distress. The Middle East respiratory syndrome (MERS) and the Coronavirus (SARS-COVID) In humans, the Coronavirus (MERS-COVID) has caused serious respiratory illness and death. Headache, sore throat, weakness, cough, muscle pain, shortness of breath, and fever are a few of the signs and side effects of COVID-19. On the other hand, chest radiological imaging, such as X-ray, is the foremost common test strategy commonly utilized for COVID-19 detection. For illustration, in [1] they appears the chest X-ray pictures taken on days 1, 4, 5, and 7 for a 50-year-old COVID-19 patient with pneumonia as illustrated in Fig.1.

Artificial intelligence (AI) algorithms are effective techniques that can play an important role in helping competent authorities (medical centres - hospitals - medical laboratories) to diagnose patients' cases and detect disease at an early time.

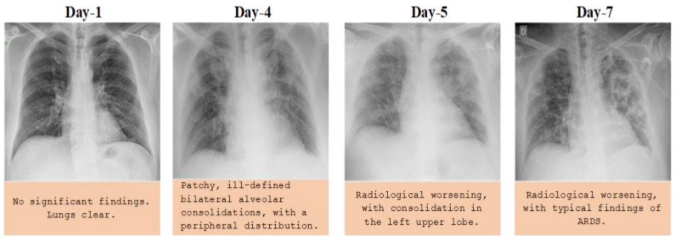


Fig.1 X-ray images for 50-years-old COVID-19 patient [1]

The motivation of this research is to introduce an automated and fast COVID-19 diagnosis system called (Automatic COVID-19 Diagnostic and Classification Intelligent System (ACDCIS)). The proposed ACDCIS has been implemented using VGG-19 [2], and ResNet50 [3] convolution neural networks (CNNs).

The rest of this paper is structured as follows. Literature reviews are presented in section 2. Section 3 presents the proposed ACDCIS system. Section 4 illustrates the system experimentation and testing. Section 5 presents a comparison and discussion of the proposed ACDCIS systems, and section 6 provides the conclusion.

II. LITERATURE REVIEW

In this section, we are going to review the previous works and methods that used ML techniques to identify and classify the covid-19. Several machine learning techniques are used to detect the Covid-19 infection using either X-ray images or CT scans images. X-ray related works

X-ray imaging makes photos of the inside of the body. There are numbers of related reviews are exists.

In [4], authors proposed dataset that consist of images of X-ray for patients related to respiratory system. To diagnosis of these pictures, it classified into two class classification (normal and covid-19) with performance 98.75% accuracy, and three class classification (covid-19 , normal, and pneumonia) with an accuracy of 93.48% using VGG-19 model. Another research [5] used ML several models with data contains of 4 classes (pneumonia, normal, other diseases and COVID-19). The performance was measured by AlexNet models with 98.82% accuracy, VGGNet with 90.13% accuracy, and RestNet with 85.98% accuracy. In [6], an automatic predictor for diagnosing COVID-19 cases is introduced to auto differentiate between the healthy people and covid-19 virus people and based on X-ray pictures. The data is divided into 2 class covid-19 and normal cases and the research includes seven traditional methods of learning (KNN, DT, SVM, ANN, RBF, CN2) and five CNN deep learning models (MobileNetV2, RestNet50, GoogleNet, DarkNet, Xception) revealed. The results are that the two best models are ANN and SVM which can be applied in diagnosing a patient if he is infected with COVID-19 virus or not all models work well, but the best accuracy is RestNet50 with 98.8% accuracy and F1 98.8%, and the SVM model got an average accuracy of 95% and F1 of 93%. By using a CNN and machine learning methods. In [7], they introduced a new standard dataset, which consists of two class classification (covid-19 and normal) cases of x-ray. A comprehensive set of tests reveal that the SRC-Dalm-based compact classifier achieves the highest accuracy of 98.52%. Moreover, DenseNet-121 outperforms other deep networks with 99.37% accuracy thanks to the CNN algorithm. Another study [8] compared the efficiency and the performance of deep learning-based CNN models like ResNet, InceptionV3, and Xception with 3 class (normal, covid-19, and pneumonia). The models ResNet, InceptionV3, and Xception have accuracy (97%, 96%, and 93% respectively) in result respectively. A. Narin, C. Kaya, and Z. Pamuk [9] introduced five CNN based models ResNet152, ResNet101, ResNet50, ResNetV2, Inception-ResNetV2, and InceptionV3 to identify of covid-19 infected patients using x-ray images. The researchers used 5-fold cross-validation to introduce three separate binary class classifications. The ResNet50 has the highest accuracy for the two-class classification (covid-19 and normal) with 96.1% of accuracy and 83.5% of F1, the two-class classification (covid-19 and viral pneumonia) achieving 99.5% of accuracy and 98.7% of F1, and two-class classification (covid-19 and bacterial pneumonia) achieving 99.7% of accuracy and 98.5% of F1. D. Wang, J. Mo, and et al.[10] used five pre-trained DL models (Xception + SVM, Xception + DT, Xception + RF, Xception + ADAboost, Xception + Bagging) to classify two classes (covid-19, and normal). The accuracy was 99.33% from Xception + SVM. In 2021, M. Faisal et al. [11] proposed two systems using the transfer-learning techniques, one system to classify the patients into two classes and the second to classify the patients into three classes. And in 2022, F. Albogamy, M. Faisal, et al. [12] introduced a system to determine the period of COVID-19 infection.

A. CT-scans related works

X-rays and computers are used in computerized tomography. CT-scan is referred as CAT-scan. In [13], four separate datasets were generated by taking patches sized 1616, 3232, 4848, and 6464 from 150 CT images of 2 class classification (normal and covid-19) for the early phase in the detection of coronavirus using ML algorithms. To improve the detection performance, they applied a process of feature extraction to patches using SVM, GLSZM, and 10-folds cross-validation, their best classification accuracy was 99.68% and an f-score of 98.58%. S. Ahuja, B. Panigrahi, and et. [14] used CNN algorithm, three-stage rotation, translation, and shearing technique for classifying the CT slices of lung into two groups non covid19 and covid19 using the ResNet-18, 50, 101, and SqueezeNet. The ResNet18 had the highest performance with 99.4% accuracy and 99.5% for F1-measure. In [15], the authors used the 3D CT volumes and a supervised software system based on CNN called DeCoVNet to classify covid-19 virus through two class classifications (normal and covid-19). After that, they used a pre-trained model called Unet to divide the lung area. They had 90.1% for accuracy. S. Kadry, V. Rajinikanth, and et. al. [16] proposed a Naive Bayes, Knn, decision tree, and linear-kernel SVM to classify the corona infection (covid-19 and normal) using CT-slices. The performance of SVM with (FFV) fused feature vector helped to obtain an accuracy of 89.80%. T. Javaheri, M. Homayounfar, and et. al. [17] created an open source series of algorithms based on CNN called CovidCTNet that successfully differentiates in CT scan output with 91.66% accuracy for two classes covid and pneumonia, and 87.5% accuracy for three classes covidm pneumonia, and normal.

M. Rahimzadeh, et al. [18] used three different deep CNNs to classify of CT images into two different classes (normal and covid). Xception and ResNet50v2-FPN models were used and had overall accuracy of 98.49% and 96.55%, respectively.

III. Proposed system

The proposed ACDCIS system consists of two sub-systems; the two-classifier system and the three-classifier system. In two-classifier system, we use a binary classification (covid-19 and normal) as shown in Fig.2.

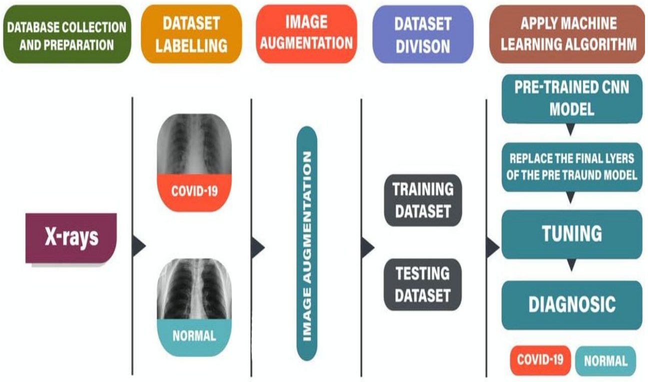


Fig.2 Proposed two-classifier- ACDCIS system.

The three-classifier system works depend on a multi-classification (covid-19, viral pneumonia, and bacterial pneumonia), as illustrated in Fig. 3.

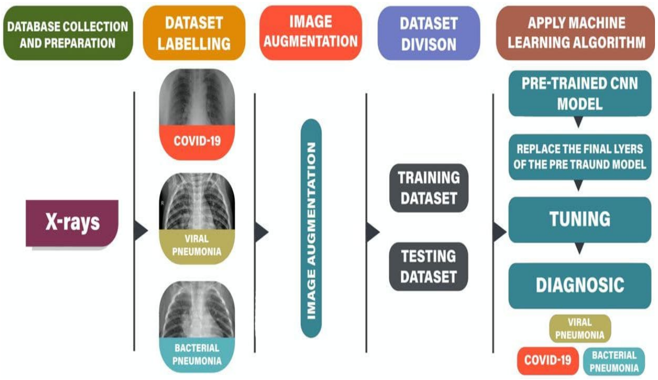


Fig.3 Proposed system of Data-A

Each system contain five stages, the first one is the database collection and preparation, which depends on x-ray images. The second stage is the dataset labelling stage, the third stage is the image augmentation, the fourth one is the dataset division which divides the dataset into two parts training and testing, the last stage is to apply the ML algorithms.

A. Database collection

In this research, we used two different datasets datasets-A and datasets-B, the first dataset [19], which used with three-classifier system, contains a total of 5185 chest x-ray images which divided into 912 covid-19 cases, 1493 viral pneumonia cases, and 2780 bacterial pneumonia cases that contain 1583 normal cases, collected in China from Guangzhou Medical Center (shown in Fig.4).

The second dataset, which used with the two-classifier systems, consists of 1995 covid-19 cases and 500 Normal cases for different patients collected in Bangladesh from Sylhet Medical College [20],Fig.5.

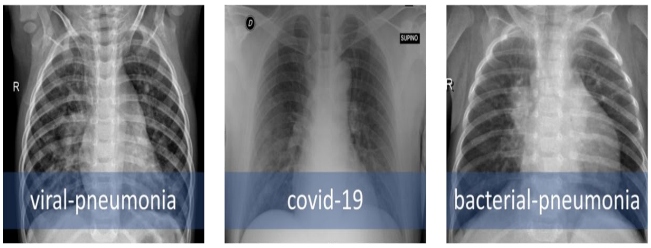


Fig.4 Sample of Data-A.

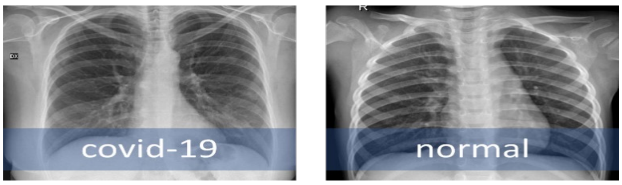


Fig.5 Samples of Data-B.

B. Dataset labelling

Dataset labeling is a group of samples of images that have been marked with one or more tags. The classification often takes a group of data and increases each part of it with a mark. It takes the process of detecting images and samples and identifying them through ML through training the system. In the images of this study, the system will recognize the images, samples and name them as either (covid-19 or normal) or (covid-19, viral pneumonia, and bacterial pneumonia) through training the system on X-rays.

C. Image augmentation (IA)

IA is a technique use to increase the size of a dataset in order to improve the model's performance. It increases the likelihood of recognition and creation of artificial training images through different methods of processing such as random rotation, reflection, cropping and transformations. In this research, we will use image augmentation for X-ray images to process and increase it into three or four times. For example, in [21] as shown in Fig.6, they use augmentation methods to increase the small COVID-19 X-ray images.

D. Dataset division

We distributed both datasets A and B into two parts (training dataset and testing dataset). The training part contain 80% of data and the testing part contain 20% of data. For data-A, The training data consist of a total of 4148 chest x-rays, which divided into 729 covid-19 cases, 1195 viral pneumonia cases, and 2224 bacterial pneumonia cases.

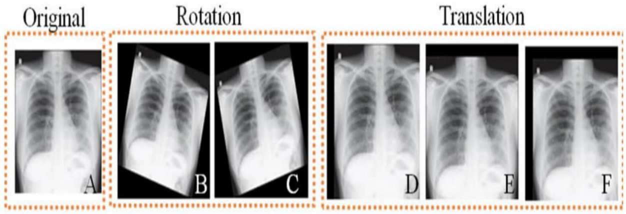


Fig.6 Example of image augmentation [21].

On the other hand, the testing data consisting a total of 1037 chest x-rays. It divided into 183 covid-19 cases, 298 viral pneumonia cases, and 556 bacterial pneumonia cases. In data-B, a total of images in training data is 1995 chest x-rays. It divided into 729 covid-19 cases and 1266 normal cases. The testing data divided to 500 images that consists of 183 covid-19 cases and 317 normal cases. Summary of cases is illustrated in TABLE I.

TABLE I DATASETS DIVISION.

		Training	Testing
Dataset-A	Covid-19	729	183
	Viral pneumonia	1195	298
	Bacterial pneumonia	2224	556
Total		4148	1037
Data-B	Covid-19	729	183
	Normal	1266	317
Total		1995	500

E. Apply machine learning algorithm

In our work, VGG-19 [2], and ResNet50 [3] architectures are used with 5-fold cross validation to detect covid-19 by using images of x-ray through two systems. For both VGG-19 and ResNet architectures, we froze all layers. After that, five extra layers we added before the last layer. First layer is Global average pooling, second layer is Dropout (0.3), third layer is Dense (128), fourth layer is Dense (64), fifth layer is softmax. In Data-A, the architecture consist of 20,098,499 parameters, 2,433,923 trainable parameters, and 17,664,576 non-trainable parameters, and ResNet architecture has total 23,858,435 parameters, 270,723 trainable parameters, and 23,587,712 non-trainable. In Data-B, the architecture of VGG-19 consisting 20,098,434 parameters, 2,433,858 trainable parameters, and 17,664,576 non-trainable parameters, and ResNet architecture has total 23,858,370 parameters, 270,658 trainable parameters, and 23,587,712 non-trainable.

IV. SYSTEM EXPERIMENTATION AND TESTING

In the proposed ACDCI system the VGG-19 [2], and ResNet50 [3] ML models are used for training and testing. The Data-A is used to classify the three-classifier system (covid-19, viral pneumonia, and bacterial pneumonia) and Data-B to classify the two-classifier system (covid-19 and normal).

The metrics, (Accuracy, F1 score, recall, and precision) are used to evaluate the VGG-19 and ResNet50 models for Data-A and Data-B, then compared it with related works. For Data-A and Data-B, we used 30 epochs and five-folds cross-validation for both VGG-19 and ResNet50. The execution performance of both Data-A and Data-B in two models was tested using datasets-A and datasets-B. As shown in TABLE II and TABLE III, the ResNet50 model outperformed with both Data-A and Data-B. For Data-A, VGG-19 model achieved accuracy of 88.12%, F1-score of 89.28%, average precision of 93%, and average recall of 86.6%, for ResNet50 accuracy was 90.05%, F1-score is 91.69%, average precision is 94.53%, and average recall is 89.13%. The details of the performance metrics of the proposed three-classifier system with Data-A is described in TABLE II:

TABLE II PERFORMANCE METRICS OF THE ACDCI- THREE-CLASSIFIER SYSTEM

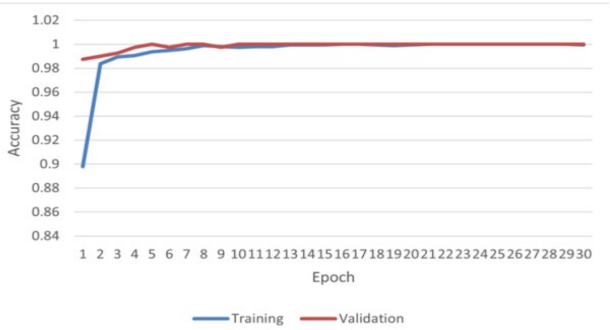
Measurements		VGG-19	ResNet50
Accuracy		88.12	**90.05**
F1-score		89.28	**91.69**
Avg. Precision		93	**94.53**
Avg. Recall		86.6	**89.13**
Precision	Covid-19	0.972	0.996
	Viral pneumonia	0.896	0.924
	Bacterial pneumonia	0.922	0.916
Recall	Covid-19	0.994	0.968
	Viral pneumonia	0.898	0.902
	Bacterial pneumonia	0.706	0.804

For the two-classifier system with Data-B, VGG-19 model achieved an accuracy of 98.6% , 98.48% of F1-score, 98% of average precision, and 98.8% for the average recall. While the ResNet50 achieved an accuracy of 99.6%, 99.55% for F1-score, 99.4% for average precision, and 99.7% for the average recall. Performance metrics of Data-B is shown in TABLE III.

TABLE III PERFORMANCE METRICS OF THE ACDCI- TWO-CLASSIFIER SYSTEM

Measurements		VGG-19	ResNet50
Accuracy		98.6	**99.6**
F1-score		98.48	**99.55**
Avg. Precision		98	**99.4**
Avg. Recall		98.8	**99.7**
Precision	Normal	0.96	0.988
	Covid-19	1.00	1.00
Recall	Normal	1.00	1.00
	Covid-19	0.976	0.994

Training performance and validation of ResNet50 with 30 epochs and fold-1 and fold-2 cross-validation for Data-B is shown in Fig.7 and Fig.8.



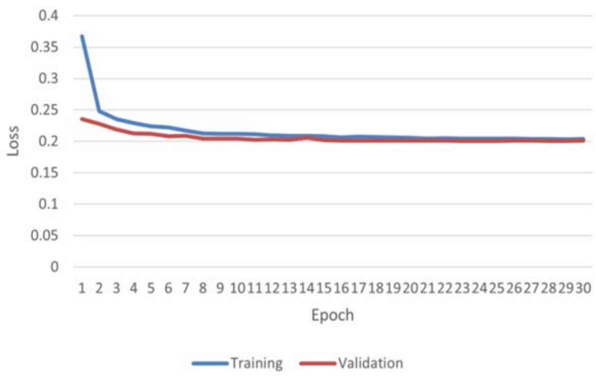


Fig.7 Performance of ResNet50 with 30 epochs and one fold cross-validation for Dataset-B

As previously mentioned, the ResNet50 got a better performance. In Fig.8, the confusion matrix of ResNet50 is shown of two folds for Data-B.

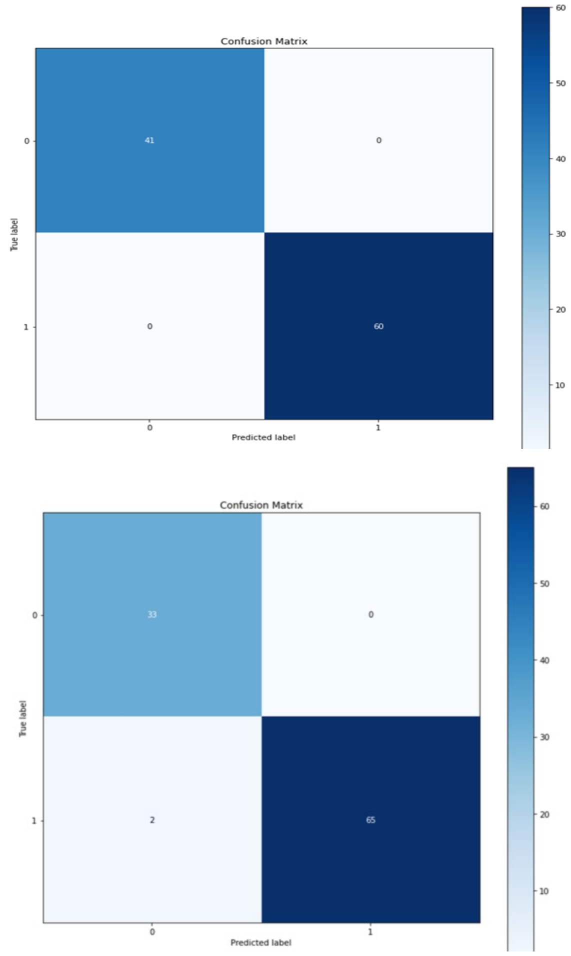


Fig.8 Confusion matrix of ResNet50 of 2 folds.

V. COMPARISON AND DISCUSSION

In this section, we compared the proposed system with related work that uses the same datasets datasets-A and datasets-B. The comparison will be based on performance metrics Accuracy, F1-score, recall, and precision. In the reference study [22], the authors detected Covid-19 based on X-rays using the same dataset that we used. The results of the comparison between our proposed system and the related work [22] are shown in table IV. In our work, the

ResNet50 model outperformed the VGG19 model and achieved superior results in all performance indicators for three-classifier system and two-classifier system with both Dataset-A and Dataset-B. As illustrated in IV, the ResNet50 for three-classifier system and two-classifier system with both Dataset-A and Dataset-B achieved better performance than reference study [22]. In Dataset-A, related work [22] used CovXNet and obtained 89.6% accuracy, 89.4% F1-score, 90.3% recall, and 88.5% precision, while the proposed three-classifier system obtained 90.05% accuracy, 91.69% F1-score, 89.13% recall, and 94.53% precision. For Dataset-B, the reference study [22] used CovXNet and achieved 97.4% accuracy, 97.1% F1 score, 97.8% recall, and 96.3% for precision, while the proposed two-classifier system obtained an accuracy of 99.6% , 99.55% of F1-score, 99.7% of recall, and 99.4% for the precision.

TABLE IV COMPARISON BETWEEN OUR STUDY AND RELATED WORK.

System	Research	Model	Accuracy	F1-score	Precision	Recall
Dataset-A	Our study	ResNet50	90.05	91.69	94.53	89.13
	Related work [22]	CovXNet	89.6	89.4	88.5	90.3
Dataset-B	Our study	ResNet50	99.6	99.55	99.4	99.7
	Related work [22]	CovXNet	97.4	97.1	96.3	97.8

VI. CONCLUSION

In this research, we introduced an Automatic COVID-19 Diagnostic and Classification Intelligent System (ACDCIS) based on ML algorithms and techniques. The proposed ACDCIS consists of two sub-systems the three-classifier system and two-classifier system. The two-classifier system was used to determine if the patient has a Covid-19 or not, while the three-classifier system was used to determine the type of infection COVID-19, bacterial infection, or virus pneumonia infection. The proposed ACDICS used two different datasets datasets-A and datasets-B. The comparison showed the superiority of the proposed ACDCIS system over the reference works with the same datasets dataset-A and dataset-B. In future work, we plan to extend the dataset by adding more COVID-19 cases and including different types of images like CT scanning images. In addition, we planned to use more epochs.

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