

Classification of COVID-19 Chest X-Ray Images Based on Speeded Up Robust Features and Clustering-Based Support Vector Machines

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Abstract – Due to the worldwide deficiency of medical test kits and the significant time required by radiology experts to identify the new COVID-19, it is essential to develop fast, robust, and intelligent chest X-ray (CXR) image classification system. The proposed method consists of two major components: feature extraction and classification. The Bag of image features algorithm creates visual vocabulary from two training data categories of chest X-ray images: Normal and COVID-19 patients' datasets. The algorithm extracts salient features and descriptors from CXR images using the Speeded Up Robust Features (SURF) algorithm. Machine learning with the Clustering-Based Support Vector Machines (CB-SVMs) multiclass classifier is trained using SURF features to classify the CXR image categories. The careful collection of ground truth Normal and COVID-19 CXR datasets, provided by worldwide expert radiologists, has certainly influenced the performance of the proposed CB-SVMs classifier to preserve the generalization capabilities. The high classification accuracy of 99 % demonstrates the effectiveness of the proposed method, where the accuracy is assessed on an independent test sets.

Keywords – COVID-19, CXR, feature extraction, SVM, SURF.

I. INTRODUCTION

As of 5 January 2021, over 88 million cases and over 1.9 million deaths due to coronavirus disease 2019 (COVID-19), caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), had been reported worldwide [1]. Early diagnosis of this disease can reduce mortality rate. People with these symptoms may have COVID-19: fever or chills, cough, shortness of breath or difficulty breathing, sore throat, congestion or runny nose, fatigue, muscle or body aches, headache, new loss of taste or smell, nausea or vomiting, and diarrhoea. Elderly and persons with chronic diseases like cancer, diabetes and lung diseases, and persons with immunodeficiency seem to be at higher risk for developing severe complications from COVID-19 illness [2]. Patients with cancer owing the epidemic COVID-19 are with severity than the general population because of the systemic immunosuppressive status caused by malignant diseases or anticancer treatment. Furthermore, patients with lung cancer are smokers with poor underlying lung conditions and low immunity. Hence, it is of vital importance to protect them from epidemic diseases during cancer treatment [3].

Chest Radiograph is the most frequently performed radiological imaging in evaluating the lungs, and may be used to help diagnose shortness of breath, persistent cough, fever, chest pain or injury, and to diagnose and monitor treatment for a variety of lung conditions such as pneumonia, emphysema and cancer. For example, Yasin et al. [4] concluded that the radiographic findings could be used as long-term consequence monitoring and predictors of COVID-19 chest manifestations. The total severity score (TSS) was estimated in the baseline and follow-up CXR and it was ranged from zero to eight. In spite of almost the availability of X-ray machines in all hospitals, a drawback is that X-ray analysis requires a radiology expert and takes considerable time which is critical when there are so many people getting sick and dying around the world from the COVID-19 pandemic.

A recent study [5] reviewed 718 cases for ambulatory patients who had tested positive for SARS-CoV-2 RT-PCR tests and also underwent CXR in Urgent Care (UC) centres between 9 March and 24 March 2020. Eleven board-certified radiologists were instructed to ignore the initial reading when they re-read the images of 636 CXRs of patients with RT-PCR confirmed COVID-19 from multiple UC centres in the greater NYC area. However, the radiologists classified these cases into two main categories: normal and abnormal chest x-rays. Their abnormal readings were classified as mild, moderate, or severe disease. There were 371 CXRs re-read as normal (58.3 %) and 265 abnormal cases (41.7 %); the ground truth of radiologists' readings indicates that 0.0 % is the incidence of false negative and 58.3 % of false positive in RT-PCR tests. However, the false-negative rate for SARS-CoV-2 RT-PCR testing is highly variable [6] and under the situation where the global pandemic of COVID-19, there is an essential need to use fast artificial intelligence (AI) methods to analyse and diagnose CXR images for COVID-19. The automated AI processes support examining patients who are taken to a hospital in order to decide who are the most seriously ill and must be treated first.

The structure of the rest of this paper is as follows. Section II provides a summary of the prepared chest X-ray datasets. Section III presents the description of the overall proposed

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framework. Section IV provides the experimental studies and discussion. Finally, the paper is concluded in Section V.

II. CHEST X-RAY DATASETS

In this study, two standard datasets were employed to validate the system performance. The benchmark dataset used in our experimental evaluation consisted of two main categories with 501 COVID-19 and 501 normal CXR images. The normal CXR images are the educational dataset publicly available on the ChestX-ray.com [7]. The COVID-19 patients developing mild to severe complications from COVID-19 illness are collected from broad image datasets from several hospitals around the world. As the confirmed COVID-19 cases available in the open-source were limited, the following selected confirmed publicly available datasets were used:

1. Cohen's multiple datasets [8] on X-rays image datasets from different institutions annotated by different clinicians or labelling tools.
2. Radiopaedia's rapidly growing, open-edit radiology resource compiled by radiologists and other health professionals from across the globe. The confirmed [9] publicly available COVID-19 CXR cases were used with 54 selected CXR images.

ChestX-ray.com was developed by Dr Jud Gurney, a world-renowned chest radiologist and faculty member at the Department of Radiology of the University of Nebraska Medical Centre (UNMC). Dr Gurney envisioned and developed ChestX-ray.com to serve as an open-source website that could teach about all things "Thoracic.". The website contains 501 consecutive normal CXR images that represent a tool to train medical student's eyes as to what a normal chest x-ray looks like. Therefore, the careful collection by the expert radiologist leads, without a doubt, to use and consider these images as the ground truth Normal CXR. Moreover, using these images in any computer method for classification will leverage the performance of the classifier while possessing the generalization capabilities. The number of the CXR images used in the training and testing experiments from both datasets is depicted in Table I.

TABLE I
NUMBER OF IMAGES IN EACH CLASS OF NORMAL AND COVID-19 CXR DATASETS

Dataset	Normal	COVID-19	Total
Training set	200	200	400
Test set	301	318	619
Total	501	518	1019

TABLE II
CLASSIFICATION ACCURACY OF CB-SVMs MODELS CONTRASTED WITH CLUSTERS (KEY POINTS) OF SURF FEATURES

Clusters (Key Points)	Average Accuracy												Evaluation
	I=1	2	3	4	5	6	7	8	9	10	Average	Standard Deviation	No. of times the Accuracy =1
10	0.89	0.92	0.91	0.913	0.87	0.9	0.898	0.89	0.87	0.91	0.897	0.0165	0
50	0.95	0.97	0.96	0.96	0.9725	0.97	0.96	0.948	0.96	0.96	0.9607	0.0083	0
100	0.9825	0.98	0.99	0.978	0.9775	0.985	0.985	0.978	0.97	0.97	0.979	0.0082	0
300	0.995	0.995	0.99	0.998	0.9925	0.995	0.99	0.9925	1	0.993	0.9905	0.003162	1
400	0.995	0.998	0.995	0.998	0.9975	0.99	0.998	0.995	1	0.993	0.9957	0.0029	1
500	0.9975	0.99	0.995	0.998	1	0.995	0.995	1	0.995	0.998	0.9963	0.0029	2
600	0.995	0.998	0.998	1	0.9925	0.995	0.998	0.995	0.995	0.995	0.996	0.0021	1
800	0.9975	0.998	0.995	0.998	0.995	0.9975	0.998	0.995	0.995	1	0.9968	0.0017	1
900	0.9975	0.998	0.998	0.998	0.995	0.9975	1	1	1	0.988	0.997	0.0037	3
1000	1	0.998	1	0.998	0.9875	1	0.995	0.9975	1	0.988	0.9963	0.0049	4
1100	1	1	0.99	0.988	0.9875	0.99	0.988	0.998	0.99	1	0.9928	0.0053	2
1500	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.9898	0.00079	0
2000	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.988	0.99	0.99	0.9898	0.00079	0

III. RELATED WORK

In the earlier research projects, COVID-19 chest X-ray images were analysed and classified using a variety of digital image processing and machine learning techniques. Furthermore, because of the vast range of variations, the privacy of the datasets, and the variety of machine learning techniques, direct comparisons between the proposed method and the associated studies are challenging. The knowledge of the many machine learning models presented in this field would

be enhanced by referring such a comparison, though. For instance, Oh et al. suggested deep learning COVID-19 features using a patch-based CNN utilizing a small training dataset [10]. Their limited training datasets have the disadvantage of decreasing classification accuracy; however, this problem is resolved by exploiting the potential biomarkers in the CXR to identify the globally distributed intensity variation that separates the features for the COVID-19. Another recent study [11] used CNN classifier and CovidGAN to generate synthetic CXR images. 85 % accuracy was achieved for classification using only CNN. The accuracy increased to 95 % with the

addition of synthetic images created by CovidGAN. Table III compares the proposed model to the relevant studies; it summarises the suggested methodology, the datasets used, and the accuracy levels attained.

TABLE III
COMPARISON OF THE RELATED STUDIES

Study	Methodology	# of images	Acc.
Oh et al. [10]	Patch-based CNN	502	88.90
Sethy et al. [11]	ResNet50+SVM	381	95.33
Ghoshal et al. [12]	Bayesian CNN (ResNet50)	5941	88.39
Wang et al. [13]	Tailored CNN	13 975	93.30
Waheed [14]	CNN+CovidGAN	1124	95.00
Afshar et al. [15]	CNN-based Capsule Networks	94 323	95.70
Apostolopoulos et al. [16]	VGG19	1427	96.78
Li et al. [17]	Discriminative cost-sensitive learning	2239	97.01
Kumar et al. [18]	CNN+PCC+ML-classifier	5984	97.87
Proposed method	BoF+SVM	1002	99.00

IV. METHODS

There are three basic steps in Chest X-ray recognition and classification: CXR feature detection, feature extraction, and then matching as illustrated in Fig. 1. These steps are the simulation of radiology expert behaviour while recognizing a CXR. Feature extraction is the primary step for CXR classification. The proposed system characterises the disease in various chest radiograph images by utilising key feature-based techniques.

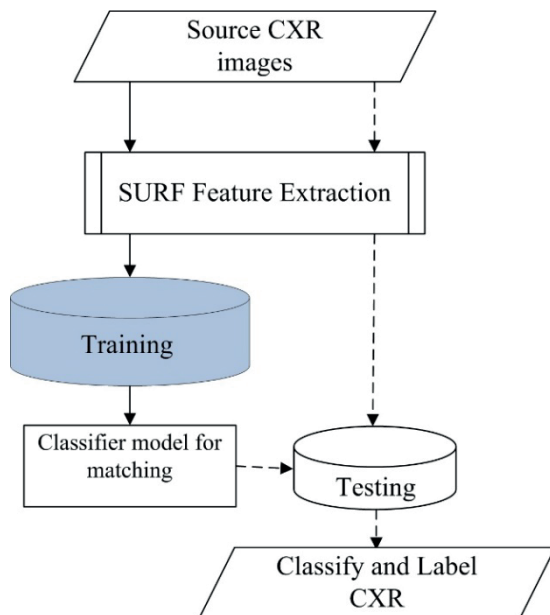


Fig. 1. Block diagram of the chest x-ray classification system.

The objective of the feature extraction technique is to transform the CXR image into a vector with a fixed dimension or a set of significant feature points with their corresponding locations. The objective is to extract and represent the intrinsic attributes of a CXR image. Then, the obtained CXR-intrinsic features are matched with an existing database of CXR-intrinsic features to perform CXR matching/classification. Feature extraction is the most important phase of the proposed CXR classification system [19]. In the present paper, feature extraction technique, namely SURF, is considered for CXR feature recognition and the Clustering-based SVMs (abbreviated as CB-SVMs) algorithms are utilized for selecting refined training sets [20].

A. Creating Bag of Features

Visual categorization with bags of key-points is adopted in this study as one of the recent techniques in computer vision problems which often facilitates large image dataset classification [21]. The method implemented in this work basically consists of four stages using Bag-of-Feature (BoF) extraction. Ideally these steps are designed to maximize classification accuracy though minimizing the computational time and will considerably speed-up the training process:

1. The Speeded-Up-Robust-Features (SURF) extraction is adopted due to the fast computational time [22]. SURF algorithm involves space theory and the feature detector is based on fast computation of Hessian matrix using integral images. SURF approximates the convolution using box filter which can be easily calculated in parallel for different scales and with the help of integral images [23].
2. Clustering feature descriptors: involves the grouping of feature descriptors into sets of clusters (vocabulary) with vector quantization algorithm using K-means.
3. Construction of a bag of features, which calculates the number of features in each cluster.
4. Classification, training bag of features as feature vectors, and assign category to the image.

The proposed method consists of two major components: feature extraction, and classification. Bag of image features algorithm creates visual vocabulary from the training data categories of CXR images. The algorithm extracts salient features and descriptors from CXR images using the SURF algorithm.

In order to collect bag of features from the two categories of CXR images, the bag of features algorithm builds visual vocabulary from the training data categories of CXR images. The bag of features is adopted in this study as one of the recent techniques in computer vision problems which often requires large amounts of image data. The bag of image features algorithm creates visual vocabulary from image training data (the categories of CXR images). The bag of features utilizes two stages for feature extraction:

- First, you select a method for picking the point locations (SURF).

- The second stage extracts the features. The feature extraction uses the SURF extractor for both point selection methods.

B. Training the SVM Image Category Classifier with Bag-of-Features

In this paper, the machine learning with the Clustering-Based Support Vector Machine (CB-SVMs) methodology is applied. The aim is to enhance the sparsity of the classifier in the presence of categorical features, leading to a gain in interpretability [24].

The clustering is improved by balancing the number of features across all image categories; by using the strongest features from each of the other image categories. The K-means clustering is used to create a bag of features by grouping it into K set of clusters (create a K word visual vocabulary). Table II demonstrates 130 training experiments of CB-SVMs models at different clusters (key points) of SURF features. The numbers of times where the average classification accuracies satisfy the value of 1.0 are reported. The nominated training set is that satisfies the maximum number of times the average training accuracy equals 1.0; when the key points equal 1000 of SURF features.

As shown in Fig. 2, the average accuracy of ten iterations of the training process is compared at different values of clusters (key points). The proposed evaluation strategy to choose the nominated training set is based on counting the number of times at which the accuracy is equal to 1.0 throughout the ten iterations of the training process (rightmost column of Table II). It is noticed that when the number of clusters is set to 1000 the average accuracy is equal to 1.0 for four iterations, Table II.

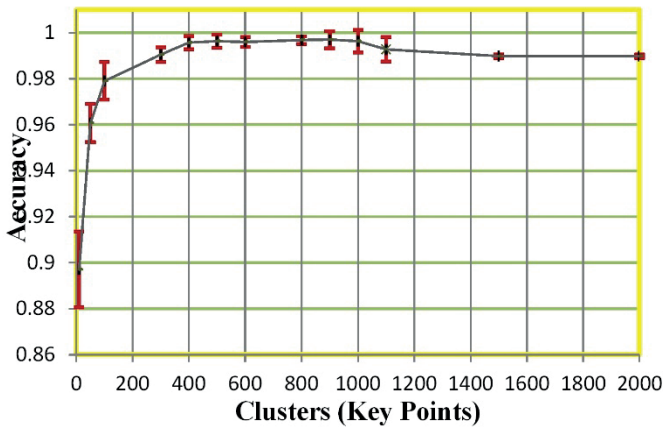


Fig. 2. Average classification accuracy of CB-SVMs models contrasted with clusters (key points) of SURF features.

The feature vectors, also known as descriptors, are categorized into a set of vocabulary with vector quantization algorithm. The SURF groups the bag of features into a set of clusters or six word visual vocabulary: scale, sign of Laplacian, orientation, location, Euclidean metric, and count of features. Figure 3 demonstrates the outputs of SURF that represent the strongest detected features that characterise the Normal and COVID-19 CXR images. The detected SURF feature points are indicated by green circles of varying size (proportional to the

scale); the strongest key points is set to ten. Despite the variability between CXR image resolutions, the SURF feature extraction has advantages in fast time response which will speed up the training time of the CB-SVMs classifier.

C. Evaluating Image Category Classifier

This is the final step of the training phase where it is necessary to evaluate the accuracy of the CB-SVMs classifier. Numerous training experiments are applied to achieve the maximum average accuracy, Table II. The normalized confusion matrix evaluates the output of the classifier: the higher the diagonal values of the confusion matrix, the better indicating rates of correct predictions. The average accuracy obtained is 1.0 (average of the diagonal elements). The MATLAB outputs of the evaluation step are listed in Fig. 4.

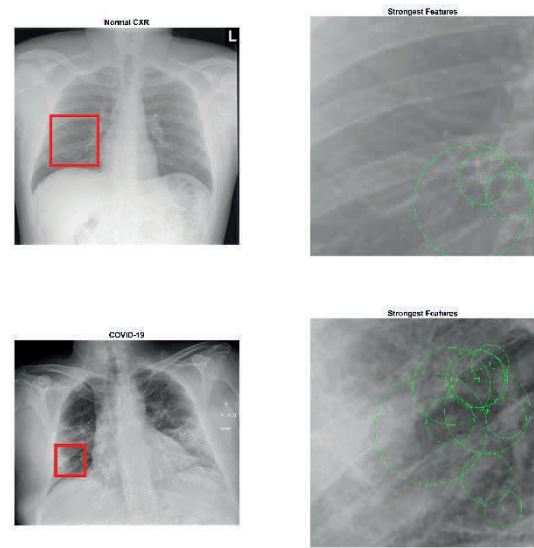


Fig. 3. Upper two images: Normal CXR and detected strongest SURF features applied to selected region of interest ROI. Lower two images: COVID-19 pneumonia in the lower lobes of the lungs and more detected strongest SURF features in the ROI.

Evaluating image category classifier for 2 categories.

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* Category 1: COVID-19
* Category 2: Normal chest x-ray

* Evaluating 200 images from category 1...done.
* Evaluating 200 images from category 2...done.

* Finished evaluating all the test sets.

* The confusion matrix for this test set is:
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KNOWN	PREDICTED	
	COVID-19	Normal chest x-ray
COVID-19	1.00	0.00
Normal chest x-ray	0.00	1.00

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* Average Accuracy is 1.00.
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Fig. 4. Normalized confusion matrix of CB-SVMs classifier for two categories.

D. Evaluation Metrics

There are also different metrics that can be used for assessing the performance of classification models, such as classification accuracy, sensitivity, specificity, precision, and F1-score. Since the current test dataset is highly imbalanced (as there is a fewer number of CXR images with COVID-19, and more CXR images that are Non-COVID), sensitivity and specificity are two proper metrics which can be used for reporting the model performance, and can be defined as:

$$\text{Sensitivity} = \frac{\sum(\text{Images correctly predicted as COVID-19})}{\sum(\text{Total COVID-19 Images})},$$

$$\text{Sensitivity} = \frac{\sum TP}{\sum TP + \sum FN},$$

$$\text{Specificity} = \frac{\sum(\text{Images correctly predicted as Normal CXR})}{\sum(\text{Total Normal CXR Images})},$$

$$\text{Specificity} = \frac{\sum TN}{\sum TN + \sum FP}.$$

The formula of the classification accuracy measure is given by:

$$\text{Accuracy} = \frac{\sum TP + \sum TN}{\text{Total samples}},$$

where TP is the true positive in case of COVID-19 case and TN is the true negative in case of Normal, while FP and FN are the incorrect model predictions for COVID-19 and Normal, respectively.

The classifier contains the number of categories and the category labels for the input trainingSets images. This step includes training the CB-SVMs classifier and encoding features for each category in the trainingSets. The appendix section lists the MATLAB code of training and testing of the CB-SVMs image category classifier.

V. RESULTS AND DISCUSSION

All our SVM model and SURF algorithm implementations are done in MATLAB; the Appendix section discusses various functions used in the training and testing steps. CB-SVMs classifiers are trained and tested with various CXR categories to evaluate the performance of the classifiers. The testing and classifying phase needs to apply the classifier onto multiple of CXR images. The “Image Batch Processor” is an easy menu or GUI that allows calling user-written function many times. From Image Batch Processor GUI the above written function ‘TestClassifier.m’ needs to be loaded. Therefore, if a user selects N images, then ‘Image Batch Processor’ will call and run ‘TestClassifier’ N times. ‘Image Batch Processor’ GUI can be started from MATLAB ‘APPS’. To process Selected/All CXR images, the green arrow on the top-left of the menu will enable repeating the call of the ‘TestClassifier’ function on the Selected/All CXR test images for classification. Figure 5 shows sample run of the “Image Batch Processor” on an input

COVID-19 CXR; which is the first case of 2019 novel coronavirus in Canada, presenting as mild pneumonia. Chest x-ray shows bilateral peribronchovascular, ill-defined opacities in all lung zones. The yellow label at the top-left corner of the classifier output CXR image indicates the result of category classification: ‘COVID-19’.

Possible blurring in chest X-ray images (e.g., Fig. 5) is tackled by the employed SURF robust feature descriptor where the interest points are invariant to scale changes, blur, rotation, illumination changes, and affine transformation.

TABLE III
TESTING CB-SVMs MODELS: AVERAGE CLASSIFICATION ACCURACY, SENSITIVITY, AND SPECIFICITY ARE CONTRASTED WITH CLUSTERS (KEY POINTS) OF SURF FEATURES

Clusters (Key Points)	Average Accuracy	Sensitivity	Specificity
10	0.864	0.850	0.877
50	0.957	0.933	0.980
100	0.957	0.943	0.943
300	0.970	0.963	0.977
400	0.975	0.970	0.980
500	0.970	0.957	0.983
600	0.987	0.983	0.990
800	0.985	0.973	0.997
900	0.982	0.967	0.997
1000	0.990	0.993	0.987
1100	0.975	0.960	0.990
1500	0.968	0.943	0.993
2000	0.967	0.940	0.993

A. Model Sensitivity and Specificity

The multiclass CB-SVMs classifier can deal with diversity of sizes and orientations of the patients in the image datasets. This is because the SURF algorithm is scale and rotation invariant; the SURF’s fixed length of CXR feature descriptor dimension (64 or extended to large feature size of 128).

The nominated training set is that satisfies the maximum number of times the average training accuracy equals 1.0; when the key points equal 1000 of SURF features. The proposed classifier is tested, key points equal 1000, by 301 COVID-19 CXR images where two CXR images are incorrectly classified as Normal. However, amongst the test dataset of 301 Normal CXR images, only three CXR images are falsely classified as COVID-19. Therefore, the classification accuracy is:

$$\text{Accuracy} = \frac{299 + 297}{301 + 301} = \frac{596}{602} = 0.990.$$

The percentage of people with COVID-19 disease is:

$$\text{Sensitivity} = \frac{299}{299 + 2} = \frac{299}{301} = 0.993.$$

The percentage of people not having the disease that test negative is:

$$\text{Specificity} = \frac{297}{298 + 4} = 0.987.$$

Table III demonstrates testing experiments of CB-SVMs models at different clusters (key points) of SURF features. The

average classification accuracy, sensitivity, and specificity satisfy are calculated.

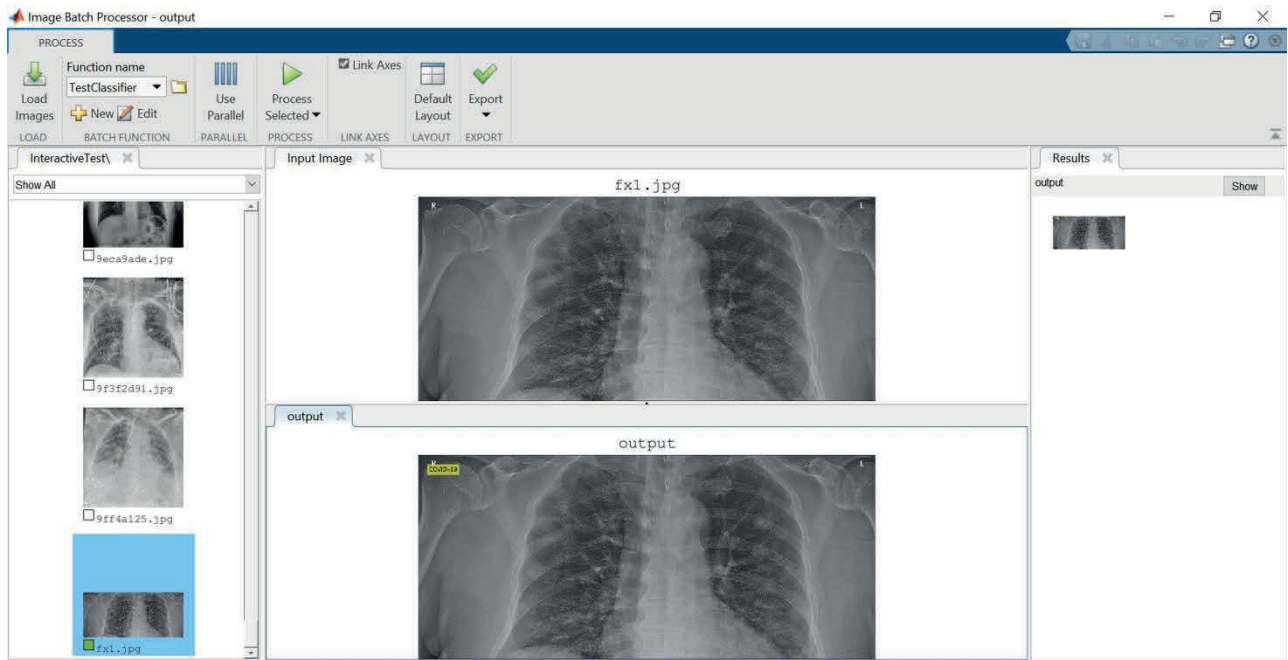


Fig. 5. The classifier outputs using the 'Image Batch Processor'. The processed CXR image is the first case of 2019 novel coronavirus in Canada [25], presenting as mild pneumonia. Chest X-ray shows bilateral peribronchovascular, ill-defined opacities in all lung zones.

As we can see, the CB-SVMs model achieves very promising results when the key points equal 1000 of SURF features and the best performing model obtains a sensitivity rate of 99.3 % and a specificity rate of 98.7 %. COVID-19 patient images are predicted to have much higher probabilities than the Normal CXR images, which is certainly encouraging, as it shows the model is learning to discriminate COVID-19 from non-COVID images. Moreover, the robustness of the classifier in the detection of COVID-19 cases will lead to high confidence and optimism in the proposed method and in fighting against this disease.

VI. CONCLUSION

In this research, Normal and COVID-19 patients' datasets have been used to test the proposed CB-SVMs intelligent chest X-ray image classification system after several iterations of training and validation. Performance results show that the trained classifier yielded the highest classification accuracy of 99 % on the blind test of Normal and COVID-19 CXR images. In particular, the CB-SVM model has detected the minimum of false positives to the covid-19 chest X-ray on the test set ($FP/TN = 2/301 = 0.997\%$). In other words, the robustness of the classifier in the detection of COVID-19 cases will lead to high confidence in the proposed method and in fighting against this disease.

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