COVID-19 Diagnostics from the Chest X-Ray Image Using Corner-Based Weber Local Descriptor

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Abstract  Corona Virus Disease-2019 (COVID-19) is a novel virus belongs to the corona virus’s family. It spreads very quickly and causes many deaths around the world. The early diagnosis of the disease can help in providing the proper therapy and saving the humans’ life. However, it founded that the diagnosis of chest radiography can give an indicator of coronavirus. Thus, a Corner-based Weber Local Descriptor (CWLD) for COVID-19 diagnostics based on chest X-Ray image analysis is presented in this article. The histogram of Weber differential excitation and gradient orientation of the local regions surrounding points of interest are proposed to represent the patterns of the chest X-Ray image. Support Vector Machine (SVM) and Deep Belief Network (DBN) classifiers are utilized for CWLD classification. Experimental results on a real chest X-Ray database showed that the gradient orientation gives the desired accuracy which is 100% using DBN classifier and CWLD size equals to 400.

Keywords COVID-19 · Chest X-Ray · Harris corners · Non-maximal suppression · WLD · Support vector machine (SVM) · Deep belief network (DBN)

1 Introduction

The novel Corona Virus Disease-2019 (COVID-19) or the Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2), as it is now known, is very fast spreading to the rest of the world from the origin of its manifestation in Wuhan City,
China Province of Hubei [1]. Around 2,418,429 confirmed cases of COVID-19 and 165,739 deaths were reported until 20 April 2020 [2]. This rapid spreading encourages the need for accurate diagnostics method that can be used in hospitals and clinics responsible for the detection of COVID-19 [3, 4].

A suspect case is characterized by sore throat, fever, and cough. In addition, the person may be suspected if he/she has a history of travel to countries with confirmed cases or contact with persons with analogous travel history or those with positive COVID-19 test. Basic diagnosis is conducted by different molecular tests on respiratory samples (for example, nasopharyngeal swab, throat swab, sputum and endotracheal aspirates). The virus can also be found in the stool and blood in extreme cases. However, cases may be asymptomatic or even don’t suffer from fever and the test may be negative even the person holds the virus [5].

Computer Tomography (CT) imaging typically reveals penetration, distortion of ground glass and convergence of sub-segments. Computerized tomographic chest screening is commonly abnormal even in those without symptoms or mild disease [6]. In fact, abnormal CT scans have been used as a second diagnose tool to identify the COVID-19 in suspect cases with negative diagnosis in molecular test. It found that many of these patients got positive molecular tests on repeat testing after some time later [7].

The main motivation of the paper is the fact that the corner-based descriptors have not been reported in COVID-19 diagnostics. To fill this research gap, this paper aims at finding the application of WLD within the local regions of points of interest during chest X-Ray analysis. The objective of the paper is to design a COVID-19 diagnostics scheme as a supplementary tool for clinical doctors. The main contributions of this work can be summarized with the following points:

1. Corner based descriptors are proposed to measure the efficiency of such type of features in COVID-19 diagnostics problem.
2. Two different types of classifiers are attempted to classify the extracted descriptors and find the optimal one based on the resulted accuracy.

The remaining of the paper is structured as follows: Sect. 2 shows a literature review for some of recently published works. Section 3 provides the detailed description of the proposed CWLD scheme for COVID-19. Section 4 illustrates the experimental results that are achieved when applying the proposed scheme on real chest X-Ray images. Finally, work conclusions and ideas for future work are presented in Sect. 5.

2 Literature Review

As soon as the disease began to spread, computer science researchers started developing systems that can detect the disease from the X-Ray image of the chest region. Following are some of these published works.
Farid et al. [8] presented a technique for recognizing the COVID-19 in CT images by proposing a Composite Hybrid Feature Extraction (CHFS). The selected features were classified by the Stack Hybrid Classification system (SHC). A total of 51 CT-images collected from Kaggle database website were used for model evaluation. An accuracy of about 96.07% has been achieved when using a Naïve Bayes as a meta-classifier in a hybrid classification.

Xu et al. [9] established an early screening model using deep learning techniques to distinguish COVID-19 pneumonia from Influenza pneumonia using CT images. A 3-dimensional deep learning model has been used to segment the CT image set. The infection type and total confidence score of this CT case were calculated with Noisy-or Bayesian function. The experiments result on a dataset consists of 1710 CT samples, including 357 COVID-19, 390 Influenza-A-viral-pneumonia, and 963 irrelevant-to-infection (ground truth) showed that the overall accuracy of the proposed system was 86.7%.

Zhang et al. [10] developed a deep anomaly detection model for COVID-19 screening. The model consists of three parts: (1) back-bone network (2) classification head, and (3) anomaly detection head. The backbone network is utilized for feature extraction task. The extracted features are then fed into the classification head and anomaly detection head, respectively. The classification head yields a “classification score”, and the anomaly detection head yields a “scalar anomaly” score. The final decision is then computed based on minimizing the entropy loss for classification and the deviation loss for anomaly detection. A database consists of 100 chest X-ray images of 70 patients with COVID-19 from the Github repository and 1431 additional 1008 chest X-ray images suffer from other pneumonia from the publicChestX-ray14 dataset. The achieved accuracy was 96.00% for COVID-19 cases and 70.65% for non-COVID-19 cases.

Elghamrawy and Hassanien [11] proposed an Artificial Intelligence-inspired Model for COVID19 Diagnosis and Prediction for Patient Response to Treatment (AIMDP) with two proposed modules: (1) Diagnosis Module (DM) and (2) Prediction Module (PM). DM has been proposed for early detecting the COVID-19 using CT scans. Convolutional Neural Networks (CNNs) has been used for the segmentation of CT image. Whale Optimization Algorithm was used for selecting the most effective features (like age, infection stage, respiratory failure, multi-organ failure and the treatment regimens). Support Vector Machine (SVM) was used for classification. An accuracy of about 97.1% has been reported using 617 CT scans chest which were collected from different resources.

Rajinikanth et al. [12] extracted the infected sections from lung CT scans due to COVID-19 using CT image segmentation. Firstly, threshold filter was applied to eliminate any possible artifacts. After that, the image is enhanced using Harmony-Search-Optimization and Otsu thresholding. Finally, the Region-Of-Interest (ROI) is located from the resulted binary image to identify level of severity by computing the pixel ratio between the lung and infection sections. Radiopedia database was used for evaluation and the results showed that the proposed method can give high priority to CT cases with high level of severity.
Although different methods were proposed, corner based descriptors have not been used in COVID-19 problem yet. By making this fact as a starting point, the proposed work aims at studying the effectiveness of such descriptors in this research issue.

3 The Proposed CWLD Scheme

As depicted in Fig. 1, the proposed CWLD scheme for COVID-19 diagnostics involves contrast enhancement, points of interest localization, WLD extraction and COVID-19 diagnostics stage. The given chest X-Ray image is firstly preprocessed by enhancing the contrast of the different intensity levels. After that, points of interest are detected and reduced in points of interest localization stage. Differential excitation and direction of gradient descriptors are then extracted from each point of interest. SVM and Deep Belief Network (DBN) classifiers are finally attempted to diagnosis the COVID-19 state based on the final descriptors. The detailed descriptions of these stages are presented in the following subsections.

Fig. 1  The general design of the proposed CWLD scheme for COVID-19 diagnostics
3.1 X-Ray Image Contrast Enhancement

Contrast enhancement stage aims at increasing the contrast of X-ray image by spreading its histogram to make full use of available intensities. Histogram Equalization (HE) is adopted for this purpose. HE increases the local contrast by spreading out the histogram, so that the new histogram is wider and more uniform in terms of distribution of each intensity. The following three steps are followed when applying HE on the chest X-Ray image [13, 14]:

1. The probability of each intensity value in the X-Ray image is firstly computed.
2. The accumulated probability is founded using probability values resulted from step 1.
3. The intensity values of X-Ray image pixels are finally remapped to the new range (i.e. [0–255]) by multiplying the accumulated probability with the maximum value of the new range (i.e., 255).

3.2 Points of Interest Localization

This stage aims at defining locations of points of interest in the X-Ray image. To meet this goal, first, all possible corners are detected. After that, the number of detected corners is reduced by suppressing non-maximal corners and selecting the strongest ones only.

3.2.1 Corner Detection

A corner can be defined as the intersection of two edges, it represents a point where the directions of these two edges change, and it is characterized by a region with intensity change in two different directions. The method that is proposed by Chris Harris and Mike Stephens [15] is employed in this work to find corner’s coordinates. Harris detects corner by taking into account the differential of the corner score with respect to direction. A shifting window is opened in any direction and the point that gives a large change in the intensity is registered as a corner. The following steps are followed to find Harris corners:

1. Firstly, the x and y derivatives ($I_x$ and $I_y$) of the contrast enhanced X-Ray image ($I$) are computed by using Sobel gradient masks ($G_x$ and $G_y$) as in the following equations:

$$I_x = G_x * I$$  \hspace{1cm} (1)

$$I_y = G_y * I$$  \hspace{1cm} (2)
where,

\[
G_x = \begin{bmatrix}
-1 & 0 & +1 \\
-2 & 0 & +2 \\
-1 & 0 & +1
\end{bmatrix}
\quad (3)
\]

\[
G_y = \begin{bmatrix}
-1 & -2 & -1 \\
0 & 0 & 0 \\
+1 & +2 & +1
\end{bmatrix}
\quad (4)
\]

* represents convolution operation.

2. After that, the products of derivatives at every pixel in the image (I) are calculated using Eqs. 5 and 6.

\[
I_x^2 = I_x * I_x \quad (5)
\]

\[
I_y^2 = I_y * I_y \quad (6)
\]

3. Then, the response of the detector (R) at each pixel I(x, y) is computed using Eq. 7.

\[
R = \det(M) - k(\text{trace}(M))^2
\]

where,

\[
M = \sum_{x,y} I(x, y) \begin{bmatrix}
I_x^2 & I_x I_y \\
I_x I_y & I_y^2
\end{bmatrix}
\quad (8)
\]

and \(\det(M)\) is the determinant of the matrix that can be founded using the following equation:

\[
\det(M) = I_x^2 I_y^2 - I_x I_y I_x I_y
\]

trace(M) is the sum of diagonal elements and can be computed as:

\[
\text{trace}(M) = I_x^2 + I_y^2
\]

k is a tunable parameter, it is usually selected from the range [0.04–0.06].

4. Finally, threshold the value of R using threshold value (T) as follows:

\[
\text{Decision}(R) = \begin{cases}
\text{Corner} & \text{if } R > T \\
\text{Non-corner} & \text{otherwise}
\end{cases}
\quad (11)
\]
3.2.2 Suppression of Non-maximal Corners

In non-maximal suppression, the number of corner points that are generated using Harris method will be reduced to $N_{\text{Best}}$ points only. The main reason behind non-maximal suppression step is to reduce the size of CWLD descriptor which in effect speeds up WLD extraction task and increases the efficiency of the resulted model in diagnostics stage. The $N_{\text{Best}}$ points are selected using the following steps:

1. For each corner point $P(x, y)$ in the image $(I)$, the fitness value is computed by opening a window of size $(5 \times 5)$ around the point and applying the following equation:

$$Fitness(P(x, y)) = \sum_{m=0}^{N_{Ws}} \sum_{n=0}^{N_{Ws}} |I(x, y) - I(x - m, y - n)|$$  \hspace{1cm} (12)

2. The corners are then sorted in ascending order based on their fitness value.
3. The first $N_{\text{Best}}$ points which give best fitness values are finally selected and considered as points of interest during WLD extraction stage.

The results of applying Harris corner detection and non-maximal suppression with $N_{\text{Best}} = 100$ are shown in Fig. 2 using an example chest X-Ray image.

3.3 WLD Extraction

WLD descriptors, which are introduced by Chen et al. [16] for texture image classification, are used for description the local regions surrounding the selected points of interest. WLD consists of two components: differential excitation and orientation of the gradient. The differential excitation component is the function of the ratio between two terms. The first term is relative intensity differences and the second one is intensity of the current pixel. Orientation of the gradient provides information about the direction of the change in intensity of the current pixel. WLD descriptors are extracted using the following steps:

1. A number of $N_{\text{Best}}$ windows with size $(N_{Ws} \times N_{Ws})$ are opened upon the contrast enhanced chest X-Ray image. The positions of these windows are determined based on the coordinates of the final selected points of interest. The coordinates of each point is considered as the centre of the opened window.
2. The differential excitation $\xi(x_c)$ for each pixel within each opened window is computed using the following equation:

$$\xi(x_c) = \arctan \left( \frac{\sum_{i=0}^{p-1} x_f - x_c}{x_c} \right)$$ \hspace{1cm} (13)
Fig. 2  Points of interest localization results, a corner detection result, b suppression of non-maximal corners

where \( x_i (i = 0, 1, \ldots, p - 1) \) denotes the ith neighbour of \( x_c \) and \( p \) is the number of neighbours.

3. The direction of gradient \( \alpha(x_c) \) is computed as:

\[
\alpha(x_c) = \tan^{-1}\left[ \frac{G_y}{G_x} \right]
\]  \hspace{1cm} (14)

where the gradient of the image pixel \( x_c \) at location \((x, y)\) is defined as:
4. The computed differential excitation and direction of gradients for all pixels are then normalized to be within the range \([0–359]\).

5. For each descriptor, a bin-based histogram is then computed and considered as the WLD descriptor for each corner point. The bin-based histogram is founded by divided the descriptor range \([0–359]\) into equal-size bins (with size \(= 45\)). Thus, the size of the resulted histogram (WLD descriptor) for each corner will be equal to 8.

6. Finally, the resulted local WLD are concatenated to form the final CWLD for the given X-Ray image.

Figure 3 demonstrates the process of CWLD extraction process.

\[
\begin{bmatrix}
G_x \\
G_y
\end{bmatrix} =
\begin{bmatrix}
\frac{\partial x_c}{\partial x} & \frac{\partial x_c}{\partial y} \\
\frac{\partial y_c}{\partial x} & \frac{\partial y_c}{\partial y}
\end{bmatrix}
\]  

(15)

3.4 COVID-19 Diagnostics

To determine whether the extracted CWLD is of positive COVID-19 or negative case, two classifiers are utilized which are SVM and DBN. SVM works by building a hyper-plane that separates the positive cases form negative ones [17]. The kernel function of SVM used in the proposed CWLD scheme is the spherical kernel because it is an anisotropic stationary kernel and has positive definite in \(R^3\). Spherical kernel function can be defined as shown in the following equation [18]:

\[
k(x, y) = \begin{cases} 
1 - \frac{3}{2} \frac{x-y}{\sigma} + \frac{1}{2} \left( \frac{x-y}{\sigma} \right)^3 & \text{if } x - y < \sigma \\
0 & \text{otherwise}
\end{cases}
\]  

(16)

On the other hand, DBN are formed by the stacked Restricted Boltzmann Machines (RBMs) that perform unsupervised learning. Once a pre-training step is
done, network weights are further fine-tuned by propagation the error backward, while the network is treated as a feed-forward net.

4 Experimental Results and Analysis

4.1 Database Description

A dataset contains 51 chest X-Ray images obtained from Kaggle website is used for system evaluation purposes. The dataset involves two classes named positive (with COVID-19) and negative (non-COVID-19). The positive class includes 39 X-Ray images collected from real cases in China, Korea, the USA, Canada, and Taiwan. On the other hand, the negative class includes 12 X-Ray images for patients suffering from MERS, SARS, and ARDS [19].

4.2 Experimental Setup

The proposed CWLD scheme has six tunable parameters: Harris parameter \( (k) \), Harris threshold value \( (T) \), number of selected corner points \( (N_{\text{Best}}) \), local window size \( (N_{\text{Ws}}) \), SVM kernel function sigma \( (\sigma) \), and number of hidden nodes in DBN \( (H) \). Based on the extensive experiments, \( k \) was obtained as 0.05, \( T \) is determined as 10,000,000, the best \( \sigma \) value was chosen as 1.5 and \( H \) was within 10 to 12. The effect of \( N_{\text{Best}} \) and \( N_{\text{Ws}} \) values on the accuracy of the proposed scheme are studied in the next subsections.

4.3 CWLD Based on Differential Excitation \( \xi(x_c) \)

The first experiment is conducted using differential excitation as WLD descriptor. Different four values for \( N_{\text{Ws}} \) and three values of \( N_{\text{Best}} \) are tested. The achieved accuracy is then computed for each combination of \( N_{\text{Best}} \) and \( N_{\text{Ws}} \) values as shown in Tables 1, 2 and 3. Hence, the accuracy is computed using the following equation [20]:

| Classifier | \( N_{\text{Ws}} = 5 \) | \( N_{\text{Ws}} = 9 \) | \( N_{\text{Ws}} = 15 \) | \( N_{\text{Ws}} = 19 \) |
|-----------|-----------------|-----------------|-----------------|-----------------|
| SVM (%)   | 94.12           | 96.08           | 96.08           | 96.08           |
| DBN (%)   | 76.47           | 88.24           | 90.02           | 88.24           |

Table 1 Results of using differential excitation descriptor with \( N_{\text{Best}} = 50 \)
Table 2  Results of using differential excitation descriptor with $N_{\text{Best}} = 100$

| Classifier | $N_{\text{Ws}} = 5$ | $N_{\text{Ws}} = 9$ | $N_{\text{Ws}} = 15$ | $N_{\text{Ws}} = 19$ |
|------------|---------------------|---------------------|---------------------|---------------------|
| SVM (%)    | 96.08               | 92.16               | 94.12               | 94.12               |
| DBN (%)    | 76.47               | 76.47               | 76.47               | 96.08               |

Table 3  Results of using differential excitation descriptor with $N_{\text{Best}} = 150$

| Classifier | $N_{\text{Ws}} = 5$ | $N_{\text{Ws}} = 9$ | $N_{\text{Ws}} = 15$ | $N_{\text{Ws}} = 19$ |
|------------|---------------------|---------------------|---------------------|---------------------|
| SVM (%)    | 98.04               | 98.04               | 98.04               | 96.08               |
| DBN (%)    | 76.47               | 82.35               | 82.35               | 92.16               |

Accuracy = $\frac{\text{Correct}}{\text{Total}}$  \hspace{1cm} (17)

where Correct is the number of the samples which are correctly classified into either positive COVID-19 or a negative case, and Total is the total number of samples in the dataset.

As obviously shown in the above tables, the best accuracy is achieved when $N_{\text{Best}} = 150$ and $N_{\text{Ws}} = 5$ using SVM as a classifier with size of CWLD = $N_{\text{Best}} (150) \times$ the size of the histogram for each corner (8) = 1200 features.

4.4 CWLD Based on Direction of Gradient $\alpha(x_c)$

Again, as with the differential excitation, four different values for $N_{\text{Ws}}$ and three different values for $N_{\text{Best}}$ are also attempted and the achieved accuracy is computed as shown in Tables 4, 5 and 6. As it is evident shown in the table, the best accuracy is reached when $N_{\text{Best}} = 50$ and $N_{\text{Ws}} = 9$ using DBN classifier and CWLD size = 400.

Table 4  Results of using direction of gradient descriptor with $N_{\text{Best}} = 50$

| Classifier | $N_{\text{Ws}} = 5$ | $N_{\text{Ws}} = 9$ | $N_{\text{Ws}} = 15$ | $N_{\text{Ws}} = 19$ |
|------------|---------------------|---------------------|---------------------|---------------------|
| SVM (%)    | 96.08               | 96.08               | 94.18               | 94.18               |
| DBN (%)    | 98.04               | 100                 | 100                 | 100                 |

Table 5  Results of using direction of gradient descriptor with $N_{\text{Best}} = 100$

| Classifier | $N_{\text{Ws}} = 5$ | $N_{\text{Ws}} = 9$ | $N_{\text{Ws}} = 15$ | $N_{\text{Ws}} = 19$ |
|------------|---------------------|---------------------|---------------------|---------------------|
| SVM (%)    | 96.08               | 96.08               | 96.08               | 96.08               |
| DBN (%)    | 74.51               | 74.51               | 92.16               | 94.12               |
Table 6  Results of using direction of gradient descriptor with N\text{Best} = 150

| Classifier | NWs = 5 | NWs = 9 | NWs = 15 | NWs = 19 |
|------------|---------|---------|---------|---------|
| SVM (%)    | 96.08   | 100     | 100     | 100     |
| DBN (%)    | 74.51   | 76.74   | 76.74   | 76.74   |

Table 7  Results of using combined $\xi(x_c)$ and $\alpha(x_c)$ descriptors with N\text{Best} = 50

| Classifier | NWs = 5 | NWs = 9 | NWs = 15 | NWs = 19 |
|------------|---------|---------|---------|---------|
| SVM (%)    | 100     | 100     | 100     | 100     |
| DBN (%)    | 82.35   | 86.27   | 92.16   | 90.20   |

Table 8  Results of using combined $\xi(x_c)$ and $\alpha(x_c)$ descriptors with N\text{Best} = 100

| Classifier | NWs = 5 | NWs = 9 | NWs = 15 | NWs = 19 |
|------------|---------|---------|---------|---------|
| SVM (%)    | 98.04   | 96.08   | 98.04   | 94.12   |
| DBN (%)    | 84.31   | 82.35   | 86.27   | 90.20   |

Table 9  Results of using combined $\xi(x_c)$ and $\alpha(x_c)$ descriptors with N\text{Best} = 150

| Classifier | NWs = 5 | NWs = 9 | NWs = 15 | NWs = 19 |
|------------|---------|---------|---------|---------|
| SVM (%)    | 98.04   | 98.04   | 98.04   | 98.04   |
| DBN (%)    | 80.39   | 78.43   | 78.43   | 78.43   |

4.5 CWLD Based on Combined $\xi(x_c)$ and $\alpha(x_c)$

The final experiment is conducted to find the effect of combining both differential excitation and direction of gradient on the achieved accuracy for the resulted models of both SVM and DBN classifiers. Tables 7, 8 and 9 show the obtained results for the same N\text{Best} and NWs values used in the previous two experiments. The best accuracy (100%) is achieved when N\text{Best} = 50 and NWs = 5 using SVM classifier with CWLD size = 800.

4.6 Results Analysis

Figures 4 and 5 illustrate the effect of N\text{Best} value on the accuracy of SVM and DBN classifiers, respectively. As shown in Fig. 4, as the value of N\text{Best} increases, the accuracy is also increases. This reflects the nature of SVM classifier that can work well with a large descriptor size by finding an optimal hyper-plane that separates the positive cases from the negative ones. In contrast, DBN classifier works in the opposite manner. As shown in Fig. 5, the accuracy decreases as long as the size of
the feature vector increases. This due to the fact that DBN works by finding patterns among the extracted features and this task becomes more complicated as the number of features increase.

4.7 Comparison with Previous Studies

Since the work on this research issue has started in a period not far away from now and the used dataset is newly collected, there are few works that can be used for comparison purpose. Table 10 shows a comparison between the proposed method
and another study that used the same dataset. As it shown in the table, the proposed scheme outperforms the work proposed by Farid et al. [8].

| Authors               | Method                                           | Accuracy (%) |
|-----------------------|--------------------------------------------------|--------------|
| Farid et al. [8]      | CHFS features and SHC classifier                 | 96           |
| The proposed scheme   | CWLD and DBN classifier                          | 100          |

5 Conclusions

Developing a computer system for COVID-19 diagnostics can improve the early detection rate of the disease and save more humans’ life. A scheme for COVID-19 diagnostics has been presented in this paper based on the CT scan of the chest region. The points of interest help in focusing the feature extraction task on the important regions within the image. Weber descriptors showed an effective role in the extraction of the regular patterns from the texture of the chest image. According to the experimental outcomes, the best accuracy (100%) achieved using direction of gradient $\alpha(x_c)$ descriptor and DBN classifier when $N_{\text{Best}} = 50$ and $N_{\text{Ws}} = 9$. As future work, feature selection techniques such as Principle Component Analysis (PCA) can be used for further reducing the extracted CWLD size. In addition, different image transformation like Gabor filter and Local Binary Patterns (LBP) can be used to highlight the most important patterns in the texture of chest image.

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