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DeSa COVID-19: Deep salient COVID-19 image-based quality assessment

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Abstract
This study offers an advanced method to evaluate the coronavirus disease 2019 (COVID-19) image quality. The salient COVID-19 image map is incorporated with the deep convolutional neural network (DCNN), namely DeSa COVID-19, which exerts the n-convex method for the full-reference image quality assessment (FR-IQA). The glaring outcomes substantiate that DeSa COVID-19 and the recommended DCNN architecture can convey a remarkable accomplishment on the COVID-chestxray and the COVID-CT datasets, respectively. The salient COVID-19 image map is also gauged in the minuscule COVID-19 image patches. The exploratory results attest that DeSa COVID-19 and the recommended DCNN methods are very good accomplishment compared with other advanced methods on COVID-chestxray and COVID-CT datasets, respectively. The recommended DCNN also acquires the enhanced outgrowths faced with several advanced full-reference-medical-image-quality-assessment (FR-MIQA) techniques in the fast fading (FF), blocking artifact (BA), white noise Gaussian (WG), JPEG, and JPEG2000 (JP2K) in the distorted and undistorted COVID-19 images. The Spearman’s rank order correlation coefficient (SROCC) and the linear correlation coefficient (LCC) appraise the recommended DCNN and DeSa COVID-19 fulfillment which are compared the recent FR-MIQA methods. The DeSa COVID-19 evaluation outshines 2.63% and 2.62% higher compared the recommended DCNN, and 28.53% and 29.01% esteem all of advanced FR-MIQAs methods on SROCC and LCC measures, respectively. The shift add operations of trigonometric, logarithmic, and exponential functions are mowed down in the computational complexity of the DeSa COVID-19 and the recommended DCNN. The DeSa COVID-19 more superior the recommended DCNN and also the other recent full-reference medical image quality assessment methods.

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Contents
1. Introduction .......................................................... 9502
2. Related Work .......................................................... 9503
3. Methods .......................................................... 9504
  3.1. Recommended DCNN Architecture .................. 9504
4. Experiments and Results ............................................. 9505
  4.1. Data Analysis .................................................. 9505
  4.2. Evaluation Measurement ................................. 9506
  4.3. DeSa COVID-19 and Recommended DCNN Experiments .................. 9506

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1. Introduction

The world health organization (WHO) released the name of the coronavirus disease 19 (COVID-19), which is classified by the international committee on taxonomy of viruses Gorbalenya et al. (2020). Many researchers and scientists enthusiastically study the COVID-19 in many aspects. It is very interesting to study the computer vision based on identifying the salient object in the COVID-19 images. The glaring objects or images can be caught by the salience detection system Achanta et al. (2009); Cheng et al. (2011) in many applications, such as image analysis Ren et al. (2014), image recognition Gao et al. (2013), image cropping Wang et al. (2019), video compression Zund et al. (2013), video segmentation Wang et al. (2018); Shen et al. (2018), and visual tracking Mahadevan and Vasconcelos (2009); Dong et al. (2019). Some salient object algorithms are exploited to get the powerful works Li et al. (2018); Chen et al. (2018); Zhang et al. (2018); Liu et al. (2018); Islam et al. (2018); He et al. (2017). Unfortunately, they have the drawbacks in recognizing the true salient objects in the undistorted and distorted images. Many handcrafted saliency detection methods Cheng et al. (2011); Jiang et al. (2013); Tong et al. (2015) are very hard to perform the image objects. At the same time, the new advanced salient object detector of convolutional neural networks (CNNs) Liu and Han (2016); Lee et al. (2016); Luo et al. (2017); Li et al. (2017); Zhu et al. (2017); Zhang et al. (2018); Wang et al. (2018); Zhang et al. (2018); Wang and Shen (2018); Guo et al. (2018); Wang et al. (2018) have admirable achievements which treat multi-layers feature fusion of CNN.

Many first-rate sophisticated methods like the edge saliency detectors Zhang et al. (2018); Liu et al. (2018); Islam et al. (2018); He et al. (2017); Liu and Han (2016); Wang et al. (2018); Zhang et al. (2017); Li et al. (2019); Jia and Bruce (2019); Xie and Tu (2015), FCN Long et al. (2015), and U-Net Ronneberger et al. (2015) study various learning scales. They explore the multi-scale saliency maps to obtain the true saliency prediction. Nonetheless, they have some drawbacks in the limited use of the interdependently multi-information of salient maps output. Instead of their drawbacks, this study comes up with the objective image quality assessment (OIQM) methods. This study treats the FR-IQA keeps a better appraisal the image object by dealing with the wanted and unwanted COVID-19 images.

In the present-day, the transfer learning in the deep learning is flourishing utilized to a countless medical image studies. The CCSSHNET model Wang et al. (2020) exercises a state-of-the-art in the transfer learning model by exploiting the discriminative correlation analysis (DCA) fusion based approach. Precendently the testing model, the proposed transfer feature learning (L2TFL) successfully eliminates the ideal layer of pre-trained CNNs. The comprehensive identification of diversified achievement outcomes, the CCSSHNET has a capable nominee for the COVID-19 image-based detection. The CCSSHNET accomplishes 97.32% of precision on the COVID-19, 96.42% of precision on the pneumonia, and 97.04% of F1-score.

Furthermore, the other state-of-the-art deep fusion approaches are FGCNet model Wang et al. (2021) which uses the learned performance. Their CNN is exploited to get the representation model of image grade. They also perform the graph convolutional net-work (GCN) to achieve an ideal representation model. This work Wang et al. (2021) also applies the multiple-way data augmentation (MDA) which uses seven distinctive data augmentation techniques. They exploit the 296 images of the COVID-19 chestxray dataset Cohen et al. (2020). Their transfer learning methods Wang et al. (2021) exceed the outstanding of investigating medical data outcomes. They reach the 97.7% and 97.1% of accuracy and sensitivity, respectively. An advanced seven-layer CNN Zhang et al. (2020) analyzes the COVID-19 diagnosis in the chest CT dataset Cohen et al. (2020). They exploit the 14-ways data augmentation during the training. They also apply the stochastic max pooling model to conquer the drawbacks of the conventional max pooling model. They are carrying out to earn 94.03%, 94.44%, 93.63% of accuracy, specificity, and sensitivity, respectively, for the 10-fold cross validation.

Explicitly, this study nominates a wider CNN, which is related to salient COVID-19 image map, we call as the deep salient COVID-19 image-based quality assessment (DeSa COVID-19). In the convolutional layers, the five-layers DeSa COVID-19 is more suitable and wider for the training algorithm than the three-layers AlexNet Krizhevsky et al. (2012). Many saliency maps in the CNN-based Oszust (2019); Zhang et al. (2016); Li et al. (2018) extract the input image to image patches. Notwithstanding, they don’t codify the human visual systems (HVS) into IQA. It is difficult for them to distinguish all of COVID-19 image patches. They also lead a lower quality appraisal to the COVID-19 image patches. LeNet Lecun et al. (1998) is an easy to understand and running well CNN for image recognition and classification. However, LeNet is not a deeper CNN, which trains a poor performance and low accuracy in a big image dataset size. AlexNet Krizhevsky et al. (2012) is a more deeper 8-layers CNN architecture which able and good performance for the RGB-image recognition. Notwithstanding, the depth of AlexNet is low execution and higher computational time in the transfer learning model. VGG Simonyan and Zisserman (2015) improves a better depth of CNN model for accuracy and speed accomplishment. It’s also one of deep learning models which has better fitting for classification in various datasets. Unfortunately, VGG suffers the disappearing gradient and slower computational accomplishment. The ResNet architecture He et al. (2015) is an essential DCNN which is not need activate all neurons of every epoch. It decreases the computational time and enhance accuracy. Unsettlingly, the intricateness VGG causes the downgrade learning. The three-layers CGNet model exploits the graph-based feature for reconstruction and classification of pneumonia datasets Yu and Wang (2021). The proposed algorithm shows a good achievement in accuracy, sensitivity, and specificity. The other transfer learning approach is data augmentation technique could be also adopted in the COVID-19 image assessment for translation, rescaling, and rotation COVID-19 images Jiang et al. (2020). In this Jiang et al. (2020) work also estimates the transfer learning speed by using Adam optimizer which is exploited in the AlexNet-based convolutional layer.

To propose the HVS, the DeSa COVID-19 contributes the convex n-square mapping model of the wanted and unwanted COVID-19
images. The convex n-square model is explored to construct the salient COVID-19 image maps which are a preferable algorithm to catch the convexness the COVID-19 image shape. Convex n-square model is also an efficient computational geometry which has an irregular COVID-19 image shape which does not have any angle 180 degrees between one and each other neighbor points. The convex n-square model has n-square shapes which means n as an unlimited number of squares. The convex n-square technique represents the original the COVID-19 image shape. This study also nominates the recommended DCNN model on the COVID-chestxray Cohen et al. (2020) and COVID-CT Zhao et al. (2020) datasets. When the X-ray ways out from the tube, the X-ray will deviate from the central ray as exploited in Wallace and Johnson (1981); Kim (2005); Lüthi et al. (2019). All borderline areas will run into a distortion type which are caused by decentralizing the anatomy to the central ray of the image receptor will suffer artifact-type distortion. The enlargement of the image receptor is not suitable for the source to image-receptor distance (SID) which has SID less than 1 meter, and the farthest of the object to image receptor distance (OID) is the pointer the greater artifact-type image distortion. While the computed tomography (CT) images have the moved distortions Zylka and Wischmann (1996); Holt (2009) like artifacts which are caused by the scanner computation and the table curving by reason of the patient’s weight. While we are facing an imbalanced COVID-19 dataset, that mean data are not representative of the authenticity situation. An imbalanced COVID-19 dataset is originally from the worse collecting data technique. The adept approaches to equipose the imbalanced COVID-19 datasets, we treat the undersampling data to retain the dominant class, and oversampling and remaking the undominant class to enlarge the outstanding. The last point, we are generating and remaking the refined data to be the new refined data of the undominant class.

The recommended DCNN model is designed in five-layers DCNN which is being a sophisticated method for COVID-19 image quality assessment in five types of distortion problems. This model also contributes to COVID-19 image quality assessment in the DeSa COVID-19 model. The DeSa COVID-19 model conducts the convex n-square algorithm to define the salient COVID-19 image area. While the recommended DCNN model in the DeSa COVID-19 model is the proposed five-layers DeSa COVID-19 which classifies and assesses the COVID-19 dataset. The DeSa COVID-19 model performance is also undoubtedly the achievement of COVID-19 image quality assessment. Its achievement is declared in the SROCC and LCC measures in the complicated COVID-19 images. This experiment exploits SROCC and LCC grades, respectively. The result demonstrates where the salient COVID-19 image maps enhance the recommended DCNN in FR-IQA. To confirm the DeSa COVID-19 performance, this study also conducts experiments on the DeSa COVID-19 architecture on the COVID-chestxray dataset and expands the DeSa COVID-19 on the COVID-CT dataset to cross-dataset appraisal. DeSa COVID-19 attains advanced outcomes on the COVID-chestxray and COVID-CT datasets.

The organization of this study is composed as subsequent: Section 1 on the page 1 is the introduction. Section 2 on the page 5 presents the related work of the DCNN architectures. Section 3 on the page 7 shows our proposed method of the recommended DCNN and Desa COVID-19 architectures, respectively. Section 4 on the page 9 presents experiments and results, and the last one is the Section 5 on the page 10 which presents the conclusion.

2. Related Work

The handcrafted salient detectors employ the artificial intelligence techniques to analyze image features Gong et al. (2015); Tu et al. (2016); Xia et al. (2017); Shen et al. (2017). They exploit the accuracy, image contrast Achanta et al. (2009); Cheng et al. (2011), regional feature of image center Jiang et al. (2013), sub-modular regional feature of image center Jiang and Davis (2013) and image background Yang et al. (2013); Zhu et al. (2014) for the salient object recognition. Besides, the salient detectors offer the CNN-based models Zhang et al. (2017); Zhang et al. (2018); Tavakoli et al. (2017); Lang et al. (2016); Li et al. (2016). At the same time, some deep learning techniques handle the region-based salient objects Lee et al. (2016); Zhao et al. (2015); Wang et al. (2015); Li and Yu (2015); Chen et al. (2016) which extract the image patches in the salient object detection. Another recent CNN-based techniques exploit multiple image saliency detection Chen et al. (2018); Zhang et al. (2018); Liu et al. (2018); Islam et al. (2018); Luo et al. (2017); Liu and Han (2016); Wang et al. (2018); Zhang et al. (2018); Zhang et al. (2017); Zeng et al. (2018); Wang et al. (2018); Wang et al. (2017); Hou et al. (2019); Chen et al. (2017); Liu and Han (2018); Liu et al. (2018); Li and Yu (2016).

The adjacent work is considered in Yang et al. (2018); Risnandar and Aritsugi (2018), which correlate to CNNs and salient image map breakthrough. The first of the dual-layer CNN model is accomplished for classification and extraction aspects. Remarkably, the Prewit model detects every edge of the image Yang et al. (2018). Unfortunately, measuring the edge can lose the significant image characteristic Barten (1999); Hulusic et al. (2017). The closer studies of the salient object Jia and Zhang (2018); Jia et al. (2017) which use the image patches appraise a threshold rate to eliminate non-salient image patches on the average weighted length [0,1]. Regrettably, these SDCNNs incorrectly appraise image quality grade. While a saliency map method Jia et al. (2017) measures FR-IQA of the salient image patches which charges more training data. FR-IQA models apply a mean structural similarity (MSSIM) Wang et al. (2004), visual information fidelity (VIF) Sheikh et al. (2005); Wang and Li (2011), and feature similarity index (FSIM) Xue et al. (2014); Moorthy and Bovik (2011). Grievously, they expose incorrect perceptual image patches quality in the distorted and undistorted images.

In medical imaging appraisal, the double stimulus continuous quality scale (DSCQS) is introduced by Rec (2002). DSCQS is the FR-IQA technique of magnetic resonance image (MRI), which observes the reference image Shiao et al. (2007); Huo et al. (2006), like ultrasound Loizou et al. (2006); Hemmsen et al. (2010) and telemedicine images Shima et al. (2007). Unfortunately, DSCQS has low responsiveness to an investigated salient image for many researchers of different countries and purposes. Therefore, DSCQS is also not suitable to HVS as a medical image appraisal.

In the last FR-IQA model of this study, an SSIM is proposed to compute the resemblances between the undistorted reference image and the testing image in the contrast, structure, and luminance Wang et al. (2004). SSIM and MSE are employed to appraise the distorted ultrasound images, namely the measurement to
structural similarity (MSSIM), which is superior to MSE score Rangaraju et al. (2012). MSSIM is only compatible with the analysis of a test image with a fine original image. Thus, MSSIM cannot be computed in real-time of the medical images appraisal.

3. Methods

3.1. Recommended DCNN Architecture

Recommended DCNN architecture is demonstrated in five convolutional layers which can probe COVID-19 image classification in FR-IQA. This work extracts the COVID-19’s image input on the size $512 \times 512$ into 11 filters in the layer-1, 5 filters in the layer-2, 3 filters in the layer-3, the layer-4, and the layer-5, respectively, by applying kernel size $7 \times 7$. The recommended DCNN criteria is described in Fig. 2. In data pre-processing, it is run by the local response normalization (LRN) in the pooling units. The input data uses the COVID-19 image size $512 \times 512$. The first to forth convolution layer train 100 channels and 25 channels are trained in the fifth convolution layer with the fully connected layer (FC layer). In the layer-1, we deploy the pooling unit with max pooling-1 which has size = 3, number of strides = 2, and the first convolutional layer has 11 filters, 16 channels, number of strides = 4, and the ELU activation function. The layer-2 has the pooling unit with max pooling-2 which demonstrates size = 3, number of strides = 2, and the second convolutional layer has 5 filters, 16 channels, number of strides = 4, and the ELU activation function. In the layer-3, we exploit the third convolutional layer which has 3 filters, 16 channels, 1 padding, and the ELU activation function. In the layer-4, we arrange the forth convolutional layer which has 3 filters, 16 channels, 1 padding, and the ELU activation function. The last layer, the layer-5, we classify the pooling unit with max pooling-3 which determines size = 3, number of strides = 2, and the fifth convolutional layer has 3 filters, 16 channels, 1 padding, and the ELU activation function. The fifth convolutional layer integrates to the FC layer-1 and 1 neuron for establishing the regression model. Whereas, the ELU function Clevert et al. (2016); Heusel et al. (2015) in Eq. (1) is more superior the learning model and computational time compared ReLU Nair and Hinton (2010), leaky ReLU (LReLU) Maas et al. (2013), and parametrized ReLU (PReLU) He et al. (2015).

$$\text{ELU}(\rho_i) = \begin{cases} \rho_i; & \rho_i \geq 0 \\ \alpha \exp(\rho_i) - 1; & \rho_i < 0 \end{cases}$$

where is the hyperparameter $\alpha$ conducts negative values COVID-19 image inputs $\rho_i$.

DeSa COVID-19 introduces the n-convex salient COVID-19 image maps as can be seen in Fig. 3. This study exploits the vertex of convex n-square which is different from Risnandar and Erwin (2020). The enlargement convexation of quadrilateral defines that
each vertex in the n-square has diagonals and the endpoints has an unlimited n number of squares. In the $D_i$, we design the diagonal shape $D_i D_j; j = 3, 4, \ldots, n - 1$ for whole n-square which has many triangles $\triangle D_i D_j; \triangle D_i D_j; i = 2, \ldots, n - 1$. Suppose $D_i(a_i, b_i); i = 2, \ldots, n$, and every triangle range $T_i$ is defined as:

$$T_i = \frac{1}{2} | \det \left( \begin{array}{cc} a_i - a_1 & b_i - b_1 \\ a_{i+1} - a_1 & b_{i+1} - b_1 \end{array} \right) |; i = 2, 3, \ldots, n - 1$$

(2)

The COVID-19 image map n-convex $T$ can be estimated the Eq. (2) as can be subsequent to:

$$T = \frac{1}{2} \sum_{i=2}^{n-1} | \det \left( \begin{array}{cc} a_i - a_1 & b_i - b_1 \\ a_{i+1} - a_1 & b_{i+1} - b_1 \end{array} \right) |; i = 2, \ldots, n - 1$$

(3)

4. Experiments and Results

4.1. Data Analysis

The largest of the readiness free-license datasets are the cluttered or imbalanced dataset, which would perturb the primary defance in the training, validating, and testing of our recommended DCNN and DeSa COVID-19 models. These trustworthy datasets are the readiness of valid, class-balanced, labeled, and salient COVID-19 dataset, like the COVID-chestxray Cohen et al. (2020) and COVID-CT Zhao et al. (2020) datasets. These COVID-19 images Cohen et al. (2020); Zhao et al. (2020) are acclimated by the recommended DCNN model for training, validating, and testing, which have 120 and 230 reference distorted COVID-19 images on the FF, BA, WG, JPEG, and JPEG2000, respectively. All of COVID-19 input images are rearranged to $512 \times 512$ pixels. The COVID-chestxray dataset is labeled by using the higher mean opinion score (MOS) in the length of $[0, 99]$ which is the better training and testing quality assessment of the recommended DCNN model in the DeSa COVID-19 model. The COVID-CT dataset is applied to cross-dataset validation and labeled by using the degradation mean opinion score (DMOS) in the length of $[0, 1]$. We also treat the data augmentation which enhances the various COVID-19 image feature learning of our recommended DCNN and DeSa COVID-19 models by constructing various distinct COVID-19 images from those training datasets. It is important that well achievement of the deep learning model observes on the large
number of training dataset. In every iteration process, data augmentation offers the random disparities of the dataset for safekeeping a good quality. We apply more data augmentation approaches in the training dataset. They are zooming, rotating, moving, width and height shifting, and the vertical and horizontal flipping. We re-train the weights of the recommended DCNN and DeSa COVID-19 models to raise the specific weights in the salient COVID-19 image quality assessment as shown in Fig. 2.

Besides data augmentation, we consider the optimal achievement by using a hyperparameters of the recommended DCNN and DeSa COVID-19 models during the iterations process. Our five convolutional layers is demonstrated in the recommended DCNN and DeSa COVID-19 models in Fig. 3.

Our five convolutional layers points out to enhance our recommended DCNN and DeSa COVID-19 models convolution because a raised number of weights, more spending time to converge, and reduction of achievement. We exploit the learning rate as the fundamental parameter in optimization process. The larger value of the learning rate overs to the swift convergence of the optimization process. Concurrently, the smaller value halts the learning process. To reach an optimal achievement, we should obtain the optimal value of the learning rate.

The other important parameter is the mini-batch size the amount of the training dataset which estimates the failure gradient of the optimization process. The mini-batch size affects the learning of the recommended DCNN and DeSa COVID-19 models acceleration. A proper value of mini-batch size is 32 in 20 times of training epochs analytically. The last, the normalization process enlarges stability of our recommended DCNN and DeSa COVID-19 models. The normalization process also scales down the covariance shift which incorporates the normalization in the rear of every convolutional and fully connected (FC) layers.

4.2. Evaluation Measurement

Fig. 1 shows the trained model which is computed on the difference COVID-19 image patches where coefficient $a = 0.1$ (yellow color) and $a = 0.6$ (red color) are the lower- and higher-coefficients of the distorted COVID-chestxray dataset validation, respectively. Fig. 2 describes our five-layers recommended DCNN architecture which is designed by using five convolutional layers and their criteria of each layer. Fig. 3 explains the DeSa COVID-19 architecture which is starting to estimate the COVID-19 image input to the n-convex salient COVID-19 image map to be the salient COVID-19 image patches (SCIP). The SCIP is executed in the recommended DCNN model to get an ideal result of COVID-19 image quality assessment. Fig. 4 represents the performance of the salient COVID-19 image map on the original and the distorted COVID-19 (blocking artifact) images, and their image patches, respectively.

The ground truth is depicted as a SROCC value on the similar set which is validated and tested by using LCC measure for 20 iterations in the COVID-chestxray and COVID-CT datasets. The distorted COVID-19 images are divided into 50% of training, 25% of validation, and 25% of testing. All undistorted COVID-19 images are reserved in the COVID-chestxray dataset. The coefficient value of distorted COVID-19 images is a set of $\left\{\frac{-250}{12}, \frac{-249}{12}, \frac{-248}{12}, ..., \frac{1}{12}\right\}$ which is correlated to $\left\{\frac{-250}{12}, \frac{-249}{12}, ..., \frac{1}{12}\right\}$ in 20 iterations. So, the saliency COVID-19 images can be obtained during the DeSa COVID-19 testing on the COVID-CT dataset.

4.3. DeSa COVID-19 and Recommended DCNN Experiments

The previous study Risnandar and Aritsugi (2018) embodies the recommended DCNN to the salient COVID-19 image map Tong et al. (2015). Coefficient $a = 0.1; 0.01; 0.0$ (red color) neglects the inappreciable COVID-19 image patches due to the DeSa COVID-19 execution as described in Fig. 1. When $a = 0$, DeSa COVID-19 represents to the recommended DCNN and otherwise but if $a > 0.6$ means DeSa COVID-19 executes on a subset. As long as training the recommended DCNN, every COVID-19 image is divided into $7 \times 7$ image patches at 20 times of training epochs which has 32 mini-batch size in length $0.01; 0.09; \frac{1}{128}$.

Table 1 endorses the rating performance of LCC and SROCC appraisals. The recommended DCNN outruns advanced full-reference-medical-image-quality-assessments (FR-MIQAs) on the salient and the unwanted COVID-19 image mapping appraisal. The recommended DCNN outperforms advanced full-reference-medical-image-quality-assessments (FR-MIQAs) on the salient and the unwanted COVID-19 image mapping appraisal.
five-types distortion. The recommended DCNN outruns the average of all FR-MIQAs in SROCC by 38.64% JPEG2000, 37.17% JPEG, and 38.41% WG, 39.70% BA, and 33.75% FF. Fortunately, the recommended DCNN runs faster than all FR-MIQAs in LCC by 34.04% JPEG2000, 38.73% JPEG, and 41.54% WG, 38.99% BA, and 38.35% FF. Table 1 demonstrates all distorted COVID-19 images in the COVID-chestxray dataset. The high performance of the recommended DCNN also surpasses all FR-MIQAs by 37.51% on SROCC and 38.33% on LCC, respectively.

Table 2 exposes the DeSa COVID-19 performance on the distinction level of the distorted COVID-19 images which is depended to the $a$ values during the SROCC and LCC measures. Horribly, the salient map work is superior performance in SROCC than LCC measure. The other, in the COVID-chestxray dataset, DeSa COVID-19

| Table 1 | Recommended DCNN: SROCC and LCC assessment [COVID-chestxray dataset]. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| SROCC [COVID-chestxray dataset] | JPEG2000 | JPEG | WG | BA | FF | ALL |
| MSSIM Wang et al. (2004) | 0.6323 | 0.6724 | 0.6882 | 0.6983 | 0.6214 | 0.6625 |
| DSCQS Rec (2002) | 0.6986 | 0.6345 | 0.6546 | 0.6742 | 0.6983 | 0.6720 |
| DMOS Angelis et al. (2007) | 0.7434 | 0.7656 | 0.7412 | 0.7216 | 0.7873 | 0.7522 |
| PDM Shiao et al. (2007) | 0.7425 | 0.7632 | 0.7214 | 0.7329 | 0.7710 | 0.7462 |
| Recommended DCNN | 0.9763 | 0.9724 | 0.9714 | 0.9873 | 0.9623 | 0.9739 |

| LCC [COVID-chestxray dataset] |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| MSSIM Wang et al. (2004) | 0.6234 | 0.6632 | 0.6731 | 0.6821 | 0.6167 | 0.6517 |
| DSCQS Rec (2002) | 0.6864 | 0.6298 | 0.6467 | 0.6622 | 0.6853 | 0.6621 |
| DMOS Angelis et al. (2007) | 0.7390 | 0.7542 | 0.7355 | 0.7198 | 0.7721 | 0.7441 |
| PDM Shiao et al. (2007) | 0.7399 | 0.7588 | 0.7133 | 0.7298 | 0.7653 | 0.7414 |
| Recommended DCNN | 0.9345 | 0.9732 | 0.9797 | 0.9708 | 0.9821 | 0.9681 |

Table 3 | DeSa COVID-19 examination: SROCC and LCC assessment of testing set [the COVID-chestxray dataset]. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| SROCC [COVID-chestxray dataset] | JPEG2000 | JPEG | WG | BA | FF | ALL |
| MSSIM Wang et al. (2004) | 0.7821 | 0.7324 | 0.7974 | 0.7325 | 0.7982 | 0.7685 |
| DSCQS Rec (2002) | 0.7325 | 0.7536 | 0.7921 | 0.7214 | 0.7214 | 0.7442 |
| DMOS Angelis et al. (2007) | 0.7723 | 0.7733 | 0.7742 | 0.7732 | 0.7787 | 0.7743 |
| PDM Shiao et al. (2007) | 0.7731 | 0.7821 | 0.7632 | 0.7408 | 0.7821 | 0.7683 |
| Recommended DCNN | 0.9721 | 0.9524 | 0.9622 | 0.9322 | 0.9432 | 0.9524 |
| DeSa COVID-19 | 0.9804 | 0.9772 | 0.9705 | 0.9809 | 0.9721 | 0.9762 |

| LCC [COVID-chestxray dataset] |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| MSSIM Wang et al. (2004) | 0.7742 | 0.7289 | 0.7821 | 0.7231 | 0.7721 | 0.7561 |
| DSCQS Rec (2002) | 0.7298 | 0.7421 | 0.7821 | 0.7109 | 0.7187 | 0.7367 |
| DMOS Angelis et al. (2007) | 0.7621 | 0.7412 | 0.7623 | 0.7611 | 0.7607 | 0.7575 |
| PDM Shiao et al. (2007) | 0.7622 | 0.7701 | 0.7590 | 0.7389 | 0.7711 | 0.7603 |
| Recommended DCNN | 0.9623 | 0.9462 | 0.9522 | 0.9209 | 0.9367 | 0.9437 |
| DeSa COVID-19 | 0.9744 | 0.9633 | 0.9603 | 0.9722 | 0.9697 | 0.9680 |

Table 4 | DeSa COVID-19 assessment: SROCC and LCC assessment [COVID-CT dataset] and trained model [COVID-chestxray dataset]. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| SROCC [COVID-CT dataset] | JPEG2000 | JPEG | WG | BA | FF | ALL |
| MSSIM Wang et al. (2004) | 0.7750 | 0.7209 | 0.7822 | 0.7209 | 0.7821 | 0.7562 |
| DSCQS Rec (2002) | 0.7287 | 0.7411 | 0.7809 | 0.7143 | 0.7132 | 0.7356 |
| DMOS Angelis et al. (2007) | 0.7634 | 0.7621 | 0.7621 | 0.7698 | 0.7624 | 0.7640 |
| PDM Shiao et al. (2007) | 0.7621 | 0.7799 | 0.7521 | 0.7378 | 0.7721 | 0.7608 |
| Recommended DCNN | 0.9653 | 0.9421 | 0.9575 | 0.9209 | 0.9366 | 0.9445 |
| DeSa COVID-19 | 0.9721 | 0.9698 | 0.9629 | 0.9741 | 0.9676 | 0.9693 |

| LCC [COVID-CT dataset] |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| MSSIM Wang et al. (2004) | 0.7609 | 0.7178 | 0.7721 | 0.7166 | 0.7608 | 0.7456 |
| DSCQS Rec (2002) | 0.7166 | 0.7352 | 0.7722 | 0.7076 | 0.7027 | 0.7269 |
| DMOS Angelis et al. (2007) | 0.7576 | 0.7378 | 0.7521 | 0.7566 | 0.7529 | 0.7514 |
| PDM Shiao et al. (2007) | 0.7541 | 0.7687 | 0.7496 | 0.7234 | 0.7632 | 0.7518 |
| Recommended DCNN | 0.9566 | 0.9309 | 0.9426 | 0.9176 | 0.9287 | 0.9353 |
| DeSa COVID-19 | 0.9687 | 0.9533 | 0.9576 | 0.9621 | 0.9571 | 0.9598 |
Comparison COVID-19 methods.

Table 5
DeSa COVID-19: pooling unit.

| Pooling unit | Fold1  | Fold2  | Fold3  | Fold4  | Fold5  |
|--------------|--------|--------|--------|--------|--------|
| SROCC        | 0.7452 | 0.8698 | 0.8821 | 0.8476 | 0.8652 |
| Overlapping max pooling | 0.6808 | 0.8265 | 0.8267 | 0.8011 | 0.8312 |
| Overlapping average pooling | 0.6465 | 0.8366 | 0.7823 | 0.8490 | 0.8312 |
| Non-overlapping Max pooling | 0.6466 | 0.8006 | 0.8012 | 0.7736 | 0.7866 |
| Non-overlapping Average pooling | 0.7042 | 0.7741 | 0.8011 | 0.8031 | 0.8267 |
| No-pooling   | 0.7921 | 0.8855 | 0.9054 | 0.8679 | 0.8721 |
| Overlapping max pooling | 0.7466 | 0.8327 | 0.8596 | 0.8197 | 0.8443 |
| Overlapping average pooling | 0.7007 | 0.8412 | 0.8265 | 0.8624 | 0.8488 |
| Non-pooling  | 0.7024 | 0.8114 | 0.8024 | 0.8276 | 0.8154 |
| No-pooling   | 0.7311 | 0.8026 | 0.8167 | 0.8304 | 0.8361 |

Table 6
Comparison COVID-19 methods.

| Methods                     | Remark                                                      |
|-----------------------------|-------------------------------------------------------------|
| MSSIM Wang et al. (2004)    | MSSIM is categorized as a full-reference COVID-19 image quality assessment (FR-CIQA). MSSIM expects that HVS is acclimated for prying the structural information from a COVID-19’s image. Its method is established on the COVID-19 image which evinces a capable addiction and these addictions dependences to take out the appropriate information regarding the structure of a COVID-19 image. This method is capable for calculating structural information of the COVID-19 image. It observs the five-type distortion which is focused to the independent of luminance, contrast, and structure. However, several drawbacks of the MSSIM are applied with the medical images, for example: suitable pooling, hard to close edges, fikleness the low variance, and inattention of the high earnestness. These MSSIM’s drawbacks are exploited to obligate the compression in the COVID-19 image, like JPEG2000 and JPEG. |
| DSCQS Rec (2002)            | DSCQS is one of the subjective COVID-19 image assessment methods of FR-CIQA. This method measures a COVID-19 image only on a human perceptual vision. However, if only a human perceptual model, an appraisal will get an approximately monotone with observed COVID-19 image quality. Factually, the original COVID-19 images are constantly accessible in DSCQS system as a reference image sequentially. However, the major disadvantage of DSCQS is the handling of a reference COVID-19 image for each sequential testing instigates DSCQS to be a higher time-computing and only a few numbers of the COVID-19 image sequential testing which can be appraised. It needs to explore different appraisal methods for the medical systems which demonstrates the different machine learning approaches. |
| DMOS Angelis et al. (2007) | DMOS, like DSCQS, is also the subjective COVID-19 image assessment method of FR-CIQA. Notwithstanding, it can be appraised that the presumed quality values from SROCC and LCC appraisals are very imprecise causes to the inconsideration of COVID-19 characteristics. |
| PDM Shiao et al. (2007)     | PDM is a subjective COVID-19 image assessment method which is mostly applied in MRI. It applies the largest possible execution rate on the COVID-19 image data acquisition. It has an efficient k-mapping traversal outcome. It also has a first-rate unique progress and flux, causes the direction is started from the k-mapping center, thus it contributes to the gradient time to all COVID-19 image structure. Nonetheless, the PDM has the drawback which uses a significant restoration method causes data are not obtained on a convex and rectilinear mapping. While, our proposed method is wider rectilinear mapping where the DeSa COVID-19 method apply the n-convex salient COVID-19 image map. |

also gains 3.07% enlightenment in the undistorted COVID-19 image by using SROCC appraisal. The highest SROCC and LCC are obtained by $\alpha = 0.6$ in the blocking artifact. The typical distortion of FF and WG achieve the highest SROCC and LCC by $\alpha = 0.1$.

Table 3 reports the DeSa COVID-19’s achievement on the COVID-chestxray dataset. In Table 3, we decide to exploit and compare the MWM Wang et al. (2004), the DSCQS Rec (2002), the DMOS Angelis et al. (2007), and the perceptual difference model (PDM) Shiao et al. (2007); Huo et al. (2006) with our DeSa COVID-19 architecture and recommended DCNN. To learn these methods Wang et al. (2004); Rec (2002), Angelis et al. (2007); ?, as can be seen from their advantages and disadvantages in Table 6. These algorithms Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007) have a similar objective image quality assessment of the full-reference (FR) image and the compressed medical images cases as reviewed in Chow and Paramesran (2016) with our proposed algorithms even though COVID-19 has occurred since the end of 2019. On all distortion types, the recommended DCNN and DeSa COVID-19 on SROCC carry out 0.9524 and 0.9762, respectively, and 0.9437 and 0.9680, respectively, on LCC measure. The recommended DCNN and DeSa COVID-19 overlap all advanced FR-MIQAs methods Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007). The DeSa COVID-19 also achieves the highest result of all. The best performance of DeSa COVID-19 is realized by coefficient $\alpha = 0.6$ on the distorted COVID-19 image (the blocking artifact) as shown in Table 2. The DeSa COVID-19 has a newfangled algorithm contrasted other FR-MIQAs algorithms Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007) as can be seen in the Table 4. The SROCC and LCC measures have 7.75% and 7.01% which transcends the others pooling unit for the overlapping max pooling as proved in Table 5.

The recommended DCNN and DeSa COVID-19 subdue for computational complexity referred among all methods Wang et al.


Table 7

Functional times (μ second) of computational complexity for shift–add operation of Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007) and prospective approaches.

| Method                | Functional times | JPEG2000 | JPEG | WG | BA | FF |
|-----------------------|------------------|----------|------|----|----|----|
| MSSIM Wang et al. (2004) | exp on [0;1.5]   | 30       | 33   | 33 | 31 | 31 |
| ln on [1;2]           | 39               | 24       | 30   | 29 | 29 | 32 |
| (sin cosh) on t=[0;5] | 29               | 30       | 30   | 28 | 31 | 31 |
| arctan[0;1]           | 31               | 31       | 30   | 27 | 25 | 25 |
| sinh[0;1]             | 24               | 25       | 28   | 23 | 29 | 29 |
| arg tanh[0;0.7]       | 25               | 26       | 29   | 25 | 27 | 27 |
| DSCQS Rec (2002)      | exp on [0;1.5]   | 26       | 21   | 24 | 25 | 23 |
| ln on [1;2]           | 25               | 27       | 22   | 26 | 23 | 23 |
| (sin cosh) on t=[0;5] | 26               | 21       | 24   | 25 | 23 | 23 |
| arctan[0;1]           | 23               | 22       | 25   | 27 | 25 | 25 |
| sinh[0;1]             | 25               | 23       | 26   | 24 | 29 | 29 |
| arg tanh[0;0.7]       | 22               | 24       | 21   | 24 | 25 | 25 |
| DMOS Angelis et al. (2007) | exp on [0;1.5] | 20       | 19   | 18 | 20 | 22 |
| ln on [1;2]           | 21               | 21       | 21   | 19 | 23 | 23 |
| (sin cosh) on t=[0;5] | 24               | 23       | 19   | 25 | 23 | 23 |
| arctan[0;1]           | 21               | 21       | 18   | 18 | 19 | 19 |
| sinh[0;1]             | 16               | 18       | 17   | 20 | 19 | 19 |
| arg tanh[0;0.7]       | 20               | 19       | 17   | 18 | 19 | 19 |
| PDM Shiao et al. (2007) | exp on [0;1.5] | 36       | 32   | 44 | 21 | 30 |
| ln on [1;2]           | 32               | 29       | 33   | 33 | 34 | 34 |
| (sin cosh) on t=[0;5] | 24               | 27       | 31   | 25 | 27 | 27 |
| arctan[0;1]           | 41               | 32       | 33   | 29 | 25 | 25 |
| sinh[0;1]             | 22               | 32       | 42   | 31 | 29 | 29 |
| arg tanh[0;0.7]       | 25               | 32       | 29   | 35 | 30 | 30 |
| Recommended DCNN      | exp on [0;1.5]   | 19       | 19   | 20 | 18 | 18 |
| ln on [1;2]           | 19               | 19       | 20   | 19 | 19 | 19 |
| (sin cosh) on t=[0;5] | 18               | 18       | 20   | 19 | 19 | 19 |
| arctan[0;1]           | 19               | 18       | 20   | 18 | 18 | 18 |
| sinh[0;1]             | 19               | 18       | 18   | 19 | 18 | 18 |
| arg tanh[0;0.7]       | 18               | 18       | 19   | 18 | 18 | 18 |
| DeSa COVID-19         | exp on [0;1.5]   | 17       | 16   | 14 | 12 | 15 |
| ln on [1;2]           | 15               | 13       | 10   | 17 | 16 | 16 |
| (sin cosh) on t=[0;5] | 14               | 12       | 15   | 16 | 14 | 14 |
| arctan[0;1]           | 13               | 15       | 12   | 16 | 14 | 14 |
| sinh[0;1]             | 15               | 14       | 12   | 15 | 14 | 14 |
| arg tanh[0;0.7]       | 16               | 13       | 12   | 14 | 15 | 15 |

(2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007) as illustrated in Table 7. The recommended DCNN and DeSa COVID-19 reduce the terms of shift and add operations. Notwithstanding, DeSa COVID-19 arises to be the top-of-the-line to the recommended DCNN and also the advanced FR-MIQAs methods Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007).

5. Conclusion

In this paper, we proposed two novel methods. They are the DeSa COVID-19 and the recommended DCNN. The DeSa COVID-19 is worked out to the salient COVID-19 image map which is incorporated with the recommended DCNN. However, the other methods disclose the improper perceptual COVID-19 image patches quality appraisal in the distorted and undistorted images due several methods are not paying attention the salient map technique. The DeSa COVID-19 has five-layer DCNN and the n-convex method exploits the full-reference image quality assessment (FR-IQA). The wider layers like the DeSa COVID-19 are more felicitous and deeper for a bigger training model. The DeSa COVID-19 employs the COVID-chestxray and the COVID-CT datasets. The recommended DCNN also earns the intensified outgrowths loaded with several advanced full-reference-medical-image-quality-assessment (FR-MQA) techniques in the fast fading (FF), blocking artifact (BA), white noise Gaussian (WG), JPEG, and JPEG2000 (JP2K) in the distorted and undistorted COVID-19 images. The DeSa COVID-19 is measured by using the SROCC and LCC.

This study offers an avant-garde recommended DCNN in FR-IQA confronted with the other advanced FR-MIQAs algorithms Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007). In SROCC, the recommended DCNN outruns 38.64% JPEG2000, 37.17% JPEG, and 38.41% WG, 39.70% BA, and 33.75% FF of all FR-MIQAs. It is also superior 34.04% JPEG2000, 38.73% JPEG, and 41.54% WG, 38.99% BA, and 38.35% FF associated all FR-MIQAs in LCC. The other contribution, DeSa COVID-19 appraisement obtain 2.63% and 2.62% more mature than the recommended DCNN, and 28.53% and 29.01% enhance than the other
advanced FR-MIQs methods Wang et al. (2004); Rec (2002); Angelis et al. (2007); Shiao et al. (2007) on SROCC and LCC, respectively. In the exercise of appraisal the proposed method outcome, we break down the datasets regarding to the COVID-19 image characteristics which have effect to the performance. The disparate five-distortion types have different characteristics. Our DeSa COVID-19 model acquires the admirable performance for all five-distortion types. The DeSa COVID-19 model higher-up the recommended DCNN model because an active role of n-convex salient COVID-19 image model.

In the subsequent time study, we would consider a joined convex-concave approach for the salient COVID-19 images-based quality estimate. The other inspection, a few researchers’ involve to the exponential, logarithmic, and trigonometric functions in the computational complexity which relates to the computational time.

Author Contributions

This work is collaborated by the author’s partnership among the Intelligent System Research Group, School of Computing, Telkom University and the Computer Vision Research Group, the Research Center for Informatics, Indonesian Institute of Sciences (LIPI) and the National Research and Innovation Agency (BRIN). The author is also the main contributors to this work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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