Novel Pre-processing Stage for Classification of CT Scan Covid-19 Images

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Abstract: An accurate evaluation of computed tomography (CT) chest images is crucial in the early-stage detection of Covid-19. The accuracy of a diagnosis is determined by the imaging modality used and the images' consistency. This paper describes a gradient-based enhancement algorithm (GCE) for CT images that can increase the visibility of the infected region. Using a multi-scale dependent dark pass filter aims to increase contrast while preserving information and edge details of the infected area. Joint occurrence between the edge details and pixel intensities of the input image is calculated to construct a cumulative distribution function (CDF). To obtain the contrast improved image, the CDF is mapped to the uniform distribution. The GCE approach is tested on the CT Covid database, and performance metrics like the contrast improvement index (CII), discrete entropy (DE), and Kullback-Leibler distance (KL-Distance) are used to evaluate the results. Compared to other techniques available in the literature, the GCE approach produces the highest CII and DE values and has more uniformity. To check the suitability of the enhancement algorithm in terms of pre-processing, a pre-trained AlexNet is employed for the classification of Covid-19 images. The finding shows an improvement of 7% in classification accuracy after enhancing the Covid-19 images using the GCE technique.

1 INTRODUCTION

Image acquisition, image processing, and image display play a role in medical image diagnosis. Various types of noise may be introduced into medical images during the acquisition process. The diagnostic process will not be possible with these images. Image enhancement methods can be used to efficiently eliminate noise and improve the quality of input images to be used for disease detection. A pre-processing phase in medical image processing is removing inherent noise from the image or enhancing the picture's contrast.Low contrast images are also insufficient for disease diagnosis (Malik et al., 2015).

Covid-19 is caused by SARS-CoV-2 and declared a pandemic by the World Health Organization (WHO) in March 2020. Covid-19 is a highly contagious virus that can lead to fatal acute respiratory distress syndrome (ARDS). Controlling the spread of Covid-19 needs early identification and diagnosis. The reverse-transcription polymerase chain reaction (RT-PCR) test is the most popular screening tool for detection. However, it is a time-consuming procedure, and several studies have shown that it has poor sensitivity in the early stages. Computer tomography (CT) and chest X-ray imaging can be used as an alternative to the RT-PCR test for precise diagnostic and various stages of disease evolution. The use of readily available imaging techniques in all Indian hospitals can be a faster and less expensive way of diagnosing Covid-19 (Nath et al., 2020).

Computed tomography (CT) imaging technology is becoming increasingly relevant in the computerized diagnostics system for medical assessment and early diagnosis. However, noise, storage, and transmission loss often disturb the digital image quality produced by recent imaging devices, which results in noisy low-contrast images that can degrade the effects of subsequent measures such as segmentation, feature extraction, and diagnosis. As a result, image quality enhancement, especially contrast enhancement, has piqued the interest of researchers over the last two decades. There are a variety of contrast enhance-

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ment techniques available, such as classical histogram equalization (HE) and others (Chi et al., 2019).

For image enhancement, Local Histogram Equalization (LHE)(Celik, 2012) is one of the most widely used techniques. The entire image is encompassed in a window in LHE, with the histogram locally equalizing the actual pixel inside the given window. Because of the complexity and variety of window sizes, several algorithms have been created to improve the efficiency of HE. In 1997, Kim developed intensity preserving bi-histogram equalization (BBHE) to address HE's mean brightness shifting issues. The input low contrast image's histogram is divided in half by the average pixel intensity, and the sub-histograms are equalized separately by BBHE (Kim, 1997).

Following Brightness preserving BHE, Dualistic Sub-Image HE (DSIHE) (Wang et al., 1999) was developed, which distinguishes the histogram of the input image by using the median value rather than the mean value. Recursive Mean-Separate Histogram Equalization (RMSHE) and Recursive Sub-Image Equalization (RSIHE) have been developed as generalization schemes for BBHE and DSIHE. RSIHE and RMSHE produce 2^r sub-histograms by recursively dividing the input histogram using the mean and median values (Sim et al., 2007). The optimum value for 'r' is the most difficult to describe. When 'r' is high, the resultant image will be nearly identical to the original image, with no enhancement (Vijayalakshmi et al., 2020).

The algorithms listed above are primarily concerned with preserving mean brightness. By incorporating clipping limits into their transformation feature, later BHE algorithms were designed to minimize over enhancement. These cutting limits are the quantitative parameters derived from the input image. (Tang and Isa, 2014). The feature-preservation BHE (CEF) process was maintained the image features through a contrast improvement. It employs gamma transformation to reduce the effect of over enhancement. It removes histogram pits using histogram addition (Wang and Chen, 2018).

Adaptive cutting limit and detail improving modifications are employed in edge enhancing BHE (Tang and Isa, 2014). Cutting limits are determined from the entropy values of the segmented histogram, and detail improvement is achieved by measuring the directed filter's linear coefficients for each pixel in the input image. Finally, the filter coefficients are used to create the enhanced image (Mun et al., 2019).

Due to the inability to use dynamic grayscale in the above-mentioned bi-histogram methods, two dimesional histogram-based methods generate images with high contrast. The intensity values with their spatial positions are employed in two -dimensional histogram-based techniques. Two-dimensional HE (2DHE) utilizes the correctly chosen spatial neighbourhood's contextual information to produce an adequately enhanced image (Celik, 2012). However, a large number of trials are required to achieve the proper size of the neighbourhood. The transformation function of spatial entropy-based contrast enhancement (SECE) utilizes the spatial location along with the number of occurrences that helps the pixels to occupy the entire dynamic range (Celik, 2014). However, it has no power over the rate of enhancement, which may result in over-enhancement (Chen et al., 2019)(Cai et al., 2018). Residual spatial entropy-based enhancement (RESE) method uses non-linear mapping based on residual entropy for contrast enhancement, which may result in a minor improvement in contrast (Celik and Li, 2016).

Joint histogram equalization (JHE) has solved the challenges of the RESE. The joint histogram (JH) measures the gray values and information in the spatial neighborhood that occur together (Agrawal et al., 2019).

As shown in the above discussion, bi-histogram approaches do not use the entire complex grayscale, resulting in minor contrast change. On the other hand, the two-dimensional histogram-based methods use the whole of dynamic grayscale, but the intensity distribution after enhancement is not standardized. In the processed picture, this results in noisy appearances.

Most of the authors have used unprocessed images for Covid-19 classification by utilizing various pre-trained networks such as AlexNet, Googlenet, VGG-16, and VGG-19, etc.,(Nath et al., 2020). However, the uneven distribution of intensities and fewer intensity values lead to poor discrimination of infected and uninfected regions in the CT scan images. Therefore, it may result in decreasing the classification accuracy of the Covid-19 diagnosis. Nevertheless, images can be pre-processed for differentiating the infected regions from uninfected regions to overcome the problem,(Jeevakala and Therese, 2018). So in this paper, a gradient-based contrast enhancement is suggested for pre-processing the CT scan Covid images.

The main goal of the GCE technique is to improve contrast while reducing artifacts, maintaining edges, and avoiding over-enhancement. The following are the critical contributions made in this paper:

1. The innovative gradient-based contrast enhancement technique approaches multiscale analysis by extracting image information at multiple levels of CT scan images.

2. A filter is used to detect essential image information and to prioritize pixel differences with their neighbours.
3. Reference and non-reference quantitative metrics verify subjective analysis of GCE technique's supremacy over traditional state-of-the-art algorithms.
4. To analyse the performance of Gradient based enhancement algorithm in the field of machine intelligence, pre-trained AlexNet is used for classification of enhanced Covid images against the unprocessed Covid images.

The remainder of the paper is structured as follows:- In Section 2, gradient based enhancement methodology and the network used for their classification are discussed. Experimental analysis of GCE technique in comparison with some of the existing contrast enhancement algorithms and the assessment of GCE in the field of machine vision are summarized in Section 3. Finally, Section 4 concludes the paper.

2 METHODOLOGY

This section describes the classification of Covid-19 from CT images of the chest by using a pre-trained AlexNet followed by a pre-processing stage. The proposed method is represented in Figure 1. First, the images are pre-processed by the gradient-based contrast enhancement algorithm. Then, the enhanced images are fed to the pre-trained network for classification.

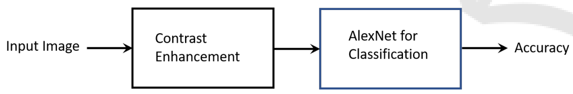

Figure 1: Block diagram for the assessment of contrast enhancement techniques.

The detail description of the blocks represented in Figure 1 is described in the following sub-sections.

2.1 Gradient based Contrast Enhancement

Gradient based contrast enhancement is divided into four sections: gradient image calculation, joint histogram computation, discrete function enumeration, and equalized histogram determination using a mapping function.

The following two measures are used to create the gradient image:

1. To obtain edge information, a filter is employed at multiple scales of the low contrast image.
2. The geometric mean value obtained from multi-scale filtered images results in a gradient image.

The decomposition of low contrast input image I is obtained by employing the Gaussian pyramid. The dimension of the input image is $M \times N$. In each subsequent image, the decimation process is utilized by halving the sampling rate. Thus, for each decomposition, a set of pictures in multi-scale will be available, including the original image.

Convoluting a 5×5 mask with the bottom level image in the pyramid yields the first level decomposed image(Burt and Adelson, 1983). Thus, the mask is denoted as:

$$m = [0.25 - 0.5a, 0.25, a, 0.25, 0.25 - 0.5a] \quad (1)$$

$$\begin{aligned} m(0) = a; m(1) = m(-1) = 0.25; \\ m(2) = m(-2) = 0.25 - 0.5a; \end{aligned} \quad (2)$$

where a is considered as 0.375. The 2-D coefficients are generated by

$$m(k,l) = m(k).m(l) \quad (3)$$

To obtain the next level $(l-1)$ image, the 2-D coefficients are convoluted with the input image and decimated by a factor of 2^{l-1}. It is denoted by:

$$J_{l-1} = \sum_{i=-2}^{2} \sum_{j=-2}^{2} m(i,j).J_l(x+i, y+j) \quad (4)$$

Images obtained from the pyramid are filtered by a dark pass filter (Wu et al., 2017). It is defined as:

$$f(x,y) = -\sum_{x',y' \in N(x,y)} \min\left(\frac{J_l(x,y) - J_l\left(x',y'\right)}{L-1}, 0\right) \quad (5)$$

where $N(x,y)$ denotes the 4-neighbours of the centre pixel (x,y) and L repesents the highest pixel intensity value of the input image. The gradient image is obtained by taking the geometric mean of filtered outputs.

$$G(x,y) = \left(\prod_{i=1}^{l} \max\left(U\left(f(x,y)\right), \varepsilon\right)\right)^{1/l} \quad (6)$$

where $U(.)$ denotes the upsampling by factor of 2^{l-1}.

The joint occurrence of the intensities is measured using the input image's distinct pixel values and the gradient image's distinct pixel values.

$$Jh = \{Jh(p,q); 1 \leq p \leq P, 1 \leq q \leq Q\} \quad (7)$$

where P and Q denotes the number of distinct gray values of the low contrast and the gradient image, respectively.

$$Jh(p,q) = \{count; for\ I(x,y) = p\ \&\ G(x,y) = q\} \quad (8)$$

From the joint occurrence, the CDF is calculated as

$$F(p,q) = \sum_{i=0}^{p}\sum_{j=0}^{q} Jh(i,j) \tag{9}$$

where $F(p,q)$ represents the CDF. The CDF is used to create a transformation which is given below:

$$Jh_{tr}(p,q) = \left\lfloor {}^{((L-1)\times(F(p,q)-F(p,q)_m))}/_{(M\times N)-1} \right\rfloor \tag{10}$$

where $\lfloor . \rfloor$ rounds the values to the closest integer, $Jh_{tr}(p,q)$ represents the equivalent pixel value which substitutes the given value whenever $I(x,y) = p$ & $G(x,y) = q$, $F(p,q)_m$ represents the smallest value of the CDF.

The mapping fuction is used to result in the enhanced image, which is denoted as:

$$JH_{tr} = \{Jh_{tr}(p,q); 1 \leq p \leq P, 1 \leq q \leq Q\} \tag{11}$$

Finally, an improved image is created by substituting equivalent intensities for the specified intensities from JH_{tr}, that comprises all equivalent intensities based on potential input and gradient image joint occurrences.

2.2 Image Classification

The enhanced images are fed to the pre-trained AlexNet for image classification. The basic building blocks of the network are convolutional, max pooling and fully connected layers. It has eight learnable layers. ReLU is used as an activation function in all layers. Output layer uses softmax activation. In this work, the tune-able parameters like mini batch size, learning rate and the number of epochs are chosen as 32, 1e-5 and 20, respectively.

3 RESULTS AND DISCUSSION

The improved visual quality of images is required in the medical imaging system for diagnosing abnormalities in any part of the human body. It is possible with the proper contrast enhancement techniques. Therefore, the image's properties, such as contrast change, artifacts, and over enhancement, are considered when comparing the image's perceived efficiency.

The gradient-based contrast enhancement approach discussed in Section 2 is tested on CT Covid image database (Zhao et al., 2020) which consists of 349 Covid and 397 non-Covid CT images collected from 216 patients. The efficacy of the GCE algorithm is analysed and compared to the methods RESE (2016), CEF (2018), EEBHE (2019), and JHE (2019) using qualitative and quantitative research. The qualitative analysis focuses on visual inspection, which provides information on annoyances, irregular enhancement, and over enhancement. Contrast improvement index (CII) for quantifying the local contrast improvement, discrete entropy (DE) for measuring the information details, Kullback-Leibler distance (KL-Distance) for measuring the uniform distribution are some of the output metrics used in quantitative research. The qualitative and quantitative analyses, as well as the findings, have been addressed in this section.

3.1 Visual Analysis

The qualitative analysis focuses on visual inspection, providing information on annoyances, irregular enhancement, and over enhancement. Figure 2 shows some examples of images taken from the Covid dataset and their histograms. The intensity levels are spread in the histogram of the sample images in a small area in the complex grayscale with an irregular spread. The pixel intensities occupy a narrow interval in the entire grayscale. It creates a minimal difference between the various objects in the image, which results in low contrast.

Figure 3 to Figure 4 display the improved images obtained by different methods. For the sample image, Figure 3 displays the contrast improved images and their respective histograms obtained through various methods of the sample image $'I1'$.

The enhanced images produced by the RESE technique are shown in Figure 3(a) and the first column of Figure 4. RESE produces an improved image with less perceived contrast in clarity, as seen in the figures. The edge information is retained after processing, but the histogram indicates that the improved image has the same range of pixel intensities as the image input, leading to minor contrast improvement than other techniques. Figure 3(b) and the second column of Figure 4 depicts the enhanced images of CEF. The local regions of images have been improved in these figures. But, the presence of histogram pits produces artifacts near the edges.

The EEBHE method has been proposed to improve edge information. Due to the directed filtering used in the EEBHE process, it is apparent from the Figure 3(c) and third column of Figure 4 that EEBHE produces enhanced images with improved edge details. However, since the resulting images use the full grayscale dynamic range with uneven distribution, it can result in minor contrast enhancement in the enhanced image's local area.

JHE provides a high contrast picture, which can

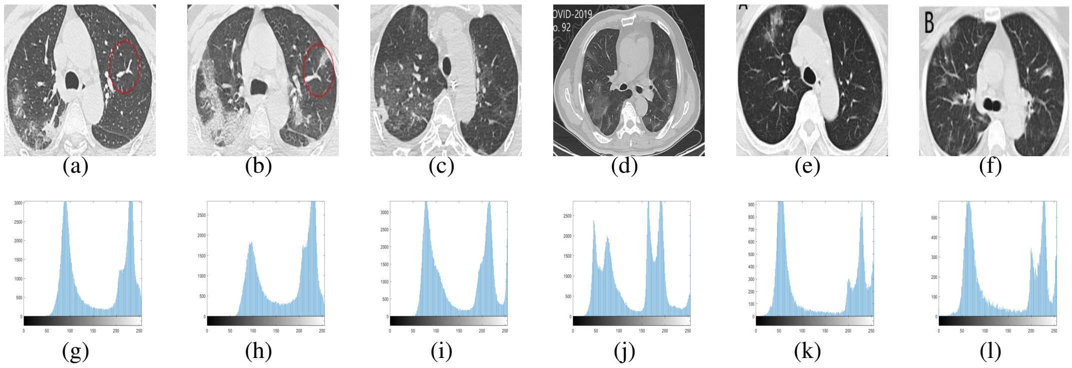

Figure 2: Sample images: (a) I1, (b) I2, (c) I3, (d) I4, (e) I5, (f) I6, (g) histogram of I1, (h) histogram of I2, (i) histogram of I3, (j) histogram of I4, (k) histogram of I5, and (l) histogram of I6.

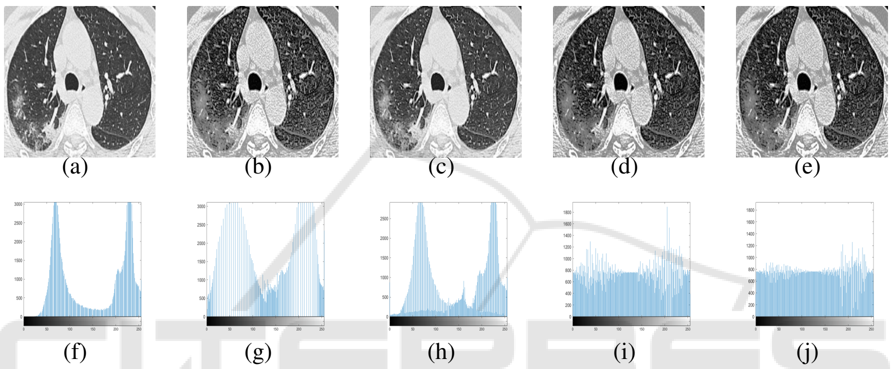

Figure 3: Contrast enhanced images of I1: (a) RESE, (b) CEF, (c) EEBHE, (d) JHE, (e) GCE, (f) histogram of RESE, (g) histogram of CEF, (h) histogram of EEBHE, (i) histogram of JHE, and (j) histogram of GCE.

be seen from Figure 3(d) and the fourth column of Figure 4. It is because it makes use of the entire complex grayscale range. However, due to average spatial neighbourhood information in the transformation, the intensities are not evenly distributed, and the resultant image is smoothed.

Figure 3(e) and the fifth column of Figure 4 display the enhanced images resulted from the GCE technique. Due to the use of multi-scale analysis and a dark pass filter, the GCE approach produces an image with increased contrast and no loss of information data. The edge information is retained in the enhanced image. It can be seen in the enhanced images' artifact-free edges. In comparison to the methods available in the literature, the GCE technique, according to the qualitative review, produces enhanced and artifact-free images.

3.2 Quantitative Analysis

Qualitative analysis resolves the potential of the enhancement methodology that human eyes justify. Quantitative analysis may be used to quantify the efficacy of the enhancement algorithms. A performance indicator accurately and automatically estimates an image's consistency. A perfect objective measure should be able to represent the subjective measure's quality predictions.

3.2.1 Contrast Improvement Index (CII)

It is possible to calculate the local contrast using CII between the input and output images. (Vijayalakshmi and Nath, 2021b; Zeng et al., 2004)

$$CII = \frac{M\left(C_{loc}\left(J\right)\right)}{M\left(C_{loc}\left(I\right)\right)} \tag{12}$$

where

$$C_{loc} = \frac{max - min}{max + min} \tag{13}$$

where max and min represent the high and low intensity values in a 3×3 window respectively. Higher CII indicates better contrast improved image.

3.2.2 Discrete Entropy

Discrete entropy measures the degree of randomness and the amount of visible information present in the

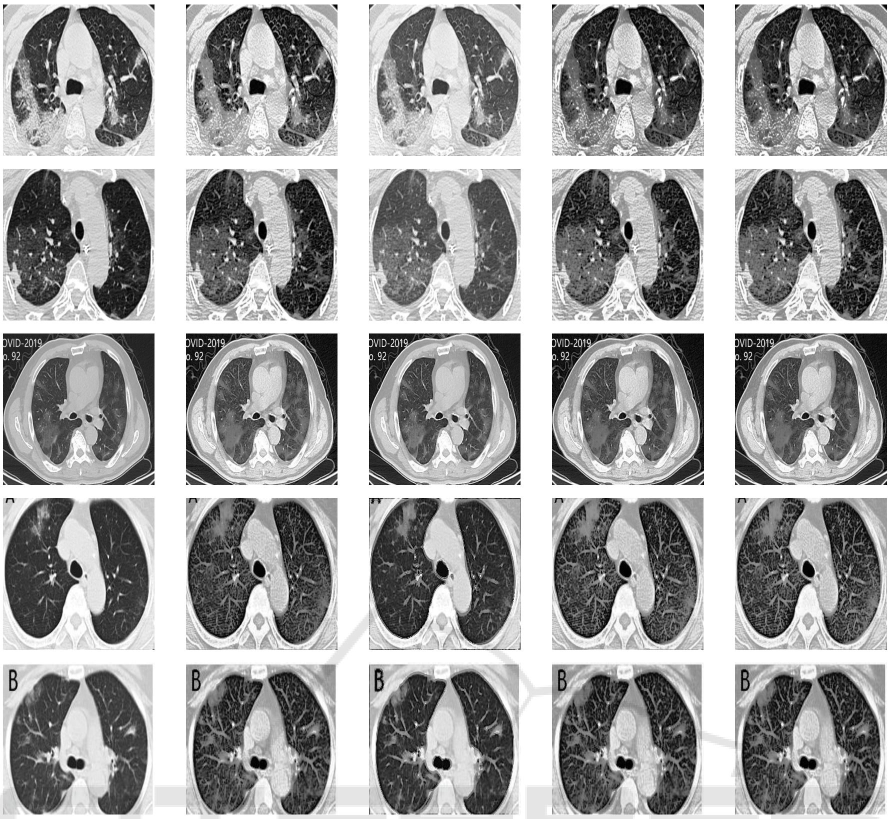

Figure 4: Contrast enhanced images obtained by various methods. First column: RESE; second column: CEF; third column: EEBHE; fourth column: JHE; and fifth column: GCE.

image (Shannon, 1948). A greater entropy value defines good information for the image. It is determined by:

$$E(I) = -\sum_{l=1}^{P} p(i_l)\log_2 p(i_l) \tag{14}$$

where $p(i_l)$ is the probability of the pixel value i_l . P indicates the total number of gray values.

3.2.3 KL-Distance

The flatness of the intensity spread in the contrast improved image is measured by the difference between the enhanced image's gray level distribution and the uniform distribution (Vijayalakshmi and Nath, 2021a). It is calculated using the Kullback-Leibler (KL) distance, as shown in equation (15). The lower KL-distance represents a uniform spread of pixel intensities.

$$KL(p,q) = \sum_{\forall k} p(y_k)\log_2\left(\frac{p(y_k)}{q(y_k)}\right) \tag{15}$$

where $p(y_k)$ and $q(y_k)$ denote the spread of the contrast improved image and uniform distribution, respectively.

Table 1: CII values of contrast enhancement technique.

Methods/ Images	RESE	CEF	EEBHE	JHE	GCE
I1	1.3	2.83	1.84	2.89	**3.03**
I2	1.7	2.5	1.23	2.8	**2.99**
I3	1.9	2.6	1.15	2.6	**2.94**
I4	1.13	1.87	1.69	1.6	**1.96**
I5	1.02	1.96	1.67	2.01	**2.19**
I6	1.00	1.97	1.71	1.96	**2.10**

Table 2: DE values of contrast enhancement technique.

Methods/ Images	RESE	CEF	EEBHE	JHE	GCE
I1	7.01	6.8	7.21	7.93	**7.96**
I2	7.10	6.84	7.17	7.8	**7.97**
I3	7.04	6.83	7.12	7.88	**7.95**
I4	7.24	7.02	7.37	7.70	**7.98**
I5	6.92	6.72	6.97	7.65	**7.97**
I6	6.90	6.85	7.2	7.67	**7.94**

All of the sample images' CII metric values are mentioned in Table 1. It shows that GCE produces high CII values as compared to the other approaches. This is because the GCE approach uses neighbour-

Table 3: KL values of contrast enhancement technique.

Methods/ Images	RESE	CEF	EEBHE	JHE	GCE
I1	0.08	0.07	0.66	0.05	**0.028**
I2	0.04	0.05	0.17	0.06	**0.02**
I3	0.09	0.08	0.44	0.08	**0.04**
I4	0.28	0.66	0.24	0.27	**0.17**
I5	0.92	0.56	0.59	0.34	**0.146**
I6	0.93	0.46	0.42	0.53	**0.053**

Table 4: Average metric values for various methods of Covid database.

Methods/ Metrics	RESE	CEF	EEBHE	JHE	GCE
CII	1.15	1.82	1.48	2.07	**2.14**
DE	6.24	6.07	6.33	7.16	**7.27**
KL	0.3	0.12	0.2	0.15	**0.05**

hood details in the mapping function to help increase the image's contrast in the surrounding area. As seen in the qualitative analysis, the entities are differentiated due to increasing contrast in the small areas.

Table 2 displays the DE values for the sample images. The GCE method results in a higher entropy value than other related methods, as observed. It is due to the use of edge information in the discrete function formulation.

Table 3 shows the KL-distance of different enhancement techniques. In comparison to the other methods, these results indicate that the proposed approach distributes intensities equally. Furthermore, it demonstrates that the GCE algorithm generates an improved image with high contrast in the absence of histogram spikes.

The GCE algorithm and methods outlined in the literature were tested on the entire database to improve the accuracy of the evaluation. For the whole database, the average values of the output metrics are tabulated in Table 4. The Table shows that the GCE algorithm improves the contrast while preserving the information details with uniform distribution of intensity values compared to the methods discussed in the literature.

Table 5: Classification accuracy values for Covid database.

Methods	Accuracy (in %)
Unprocessed	73.32
RESE	75
CEF	74
EEBHE	76.04
JHE	78.72
GCE	**80.6**

3.2.4 Assessment of GCE in Machine Intelligence

A pre-trained AlexNet is used to investigate the efficiency of a gradient-based contrast enhancement algorithm in the field of machine intelligence. For covid detection, the CT scan Covid and non-Covid images are used.

The assessment is carried out in the following two phases. In the first phase, the AlexNet is trained and tested with the images without enhancement. For training, 80% of Covid images and non-Covid images are provided to the network. The remaining 20% of images from the two classes are tested. As a result, the network offers classification accuracy of 73% in images without enhancement.

In the second phase, the network is trained and tested with 80% and 20% of the pre-processed images, respectively. The contrast enhancement algorithms discussed in the literature and the gradient-based contrast enhancement method are used as a pre-processing stage. Table 5 shows the classification accuracy of unprocessed and enhanced Covid-19 images of various methods. It is inferred from Table 5 that enhanced images help in improving the classification accuracy. It is observed that with GCE, the classification accuracy is 80.62%, which is the highest value when compared to the other techniques discussed in the literature. Therefore, it may be concluded that the GCE algorithm aids in the improvement of classification accuracy of CT scan Covid-19 images.

4 CONCLUSIONS

In this paper, a pre-processing stage for improving the classification accuracy of Covid-19 CT scan images is described. It uses gradient-based contrast enhancement (GCE) as a pre-processing stage. In GCE, the mapping function uses the joint distribution of edge information and intensity values to map the pixel values to fill the complete grayscale with a uniform spread. It has been shown that the method can increase contrast by reducing histogram peaks and pits, resulting in artifact-free contrast improved images. The method outperforms increasing contrast, avoiding loss of information, and ensuring a consistent distribution of gray levels, which can be seen in the histogram and measured using the KL-distance. Furthermore, a pre-trained AlexNet is used to investigate the efficacy of a gradient-based contrast enhancement algorithm. After increasing the contrast of the images using GCE, the classification accuracy is improved from 73.32% to 80.62%, according to the results. Hence, it may be concluded that the GCE algorithm can be used as a pre-processing stage for improving the classification accuracy of CT scan Covid-19 images.

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