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Enhancement of Medical Images Using Super Resolution Convolutional Neural Network

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Abstract

The high contrast for images taken of a human body by the medical apparatuses is quite important to diagnose the patient case perfectly. In this paper, a strategy for enhancing the contrast of Computed Tomography (CT scan) and Magnetic Resonance Imaging (MRI) is suggested. The strategy consists of two stages: pre-processing and then enhancement, either using Gaussian blur or not. The pre-processing stage involves an image smoothing, convert the image color space from RGB to YC_rC_b. The brightness compound (Y) is implied withe the Supper Resolution Convolution Neural Network (SRCNN) in order to raise image resolution, and then the images are returned to color space RGB using transformation equations. The measures of Peak-Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Square Error (MSE) and Universal Quality index (UQI) were used to assess the quality of enhanced images. According to the results, when a Gaussian filter is utilized, a higher resolution image is obtained, both in term of subjective or objective assessment. The use of a high-resolution convolutional neural network to enhancement medical images helps to detect tumors in early stages, and therefore the proposed system will help save human life.

Keywords: Medical images, Interpolation, Gaussian filter, Color spaces RGB, Color space YC_bC_r, SRCNN.

تحسين صور طبية باستخدام الشبكة العصبية الالتفافية فائقة الدقة

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الخلاصة

يعد التباين العالي للصور المأخوذة لجسم الانسان بواسطة الاجهزة الطبية امرا مهما جدا لتشخيص حالة المريض بشكل مثالي. في هذا البحث تم اقتراح الية لتحسين تباين التصوير المقطعي (CT scan) وتصوير الرنين المغناطيسي (MRI) تتكون الالية المقترحة من مرحلتين هي المعالجة الاولية ثم التحسين، اما باستخدام مرشح كاوس او بدون استخدامه تتضمن مرحلة المعالجة الاولية تنعيم الصور، تحويل الفضاء اللوني للصور من RGB الى YC_rC_b. يتم تضمين مركب الاضاءة Y مع الشبكة العصبية الالتفافية فائقة الدقة (SRCNN) من اجل زيادة دقة الصورة ثم يتم اعادة الصورة الى الفضاء اللوني RGB باستعمال معادلات التحويل. تم استخدام مقاييس نسبة ذروة الاشارة الى الضوضاء، معامل التشابه التركيبي، معدل مربع الخطأ، معامل الجودة الشامل لتقييم جودة الصور المحسنة وفقا للنتائج عند استخدام مرشح كاوس يتم الحصول على صورة بدقة اعلى سواء من حيث التقييم الذاتي او الموضوعي. ان استخدام الشبكة العصبية الالتفافية فائقة الدقة في تحسين الصور الطبية يساعد على اكتشاف الاورام في مراحل مبكرة ولذلك النظام المقترح سوف يساعد على انقاذ حياة الانسان.

الكلمات المفتاحية: الصور الطبية، الاستكمال، مرشح كاوس، الفضاء اللوني RGB، الفضاء اللوني YC_rC_b، الشبكة العصبية الالتفافية فائقة الدقة SRCNN.

Introduction

There are many factors affecting the diagnostic medical images, which are internal and external factors. The internal factors are related to the body tissue subject to examination in terms of the atomic number and density of the tissue. While the external factors are related to the mechanism of the device˒s work. Using convolutional neural networks to deal with SR problems mimics the processing of the human visual system. There- fore, computer vision is a good applications of neural net- works. Super-resolution is a classic application of computer vision, and tends to produce images that people find either realistic or aesthetically pleasing [1].

Interpolation

Digital image processing is simply an approach of treating an image and enhancing its appearance utilizing the computer algorithms. Various techniques can be utilized to do that treatment; image interpolation is one of them [2]. Image interpolation is used to convert a low-resolution image (LR) into a high-resolution one (HR) which presents more details and hence, better perceptual quality. This technique can be employed in many applications like HD videos, medical image, and satellite imaging [3]. Many different techniques of interpolation are mostly used, like;

A. Nearest Neighbor

Nearest neighbor technique is the simplest interpolation approach in which each pixel in the output image is interpolated by allocating values of the nearest point in the input image. The interpolation kernel for the nearest neighbor [1].

$$\boldsymbol{h}(\boldsymbol{x}) = \begin{cases} \mathbf{0} & |\boldsymbol{x}| > \mathbf{0} \\ \mathbf{1} & |\boldsymbol{x}| < \mathbf{0} \end{cases} \qquad \mathbf{(1)}$$

This technique is also named as pixel replication and point shift algorithm [4].

B. Bilinear Interpolation

This interpolation method implies calculating the final value of pixels' average by weighting the average of the four surrounding area pixels to recount input coordinates and allocate that mean value to the output coordinates. This technique achieves interpolation in both the horizontal and vertical directions. The interpolation kernel for bilinear interpolation is as following [5].

$$u(x) = \begin{cases} 0 & |x| > 1 \\ 1 - |x|, & |x| < 1 \end{cases} \quad (2)$$

The distance between the interpolated point and grid point is denoted by x.

C. Bicubic Interpolation

Bicubic interpolation is usually adopted in image resampling rather than bilinear interpolation or nearest neighbor in the case of the process speed is not concerned [1]. The bicubic convolution interpolation kernel is [5]:

$$W(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1 & for\ |x| \le 1 \\ a|x|^3 - 5a|x|^2 + 8a|x| - 4a & for\ 1 < |x| < 2 \\ 0 & other\ wise \end{cases} \quad (3)$$

Where a is generally taken as -0.5 to –0.75, x is the gray level value.

Image Enhancement

The filter at a specified pixel (x, y) has a specified response which is calculated at the same pixel using a predefined relationship. The digital image processing involves several spatial filters that are utilized in image enhancement such as; Gaussian filter is a linear function that is used to extract noise and blur from the image and hence, improve the image resolution. Basically, the Gaussian function which utilized to enhance images is described in equation (4) [6]:

$$G(x) = 1/\sqrt{2\pi\sigma^2}\, e^{-x^2/2\sigma^2} \quad (4)$$

Where $G(x)$ is the output image, σ is the standard deviation of the distribution, it plays an important role in its behavior. The distribution is supposed to have a mean of 0.

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Super-resolution Convolutional Neural Network (SRCNN)

The super-resolution convolutional neural network (SRCNN) is considered one of the state-of-the art deep learning-based SR methods. Single image super- resolution (SR) approach can reproduce a high-resolution image (HR) from a low-resolution image (LR) by improving the resolution of the image. In the medical imaging with an HR display, HR images are anticipated to deliver more accurate diagnosis [7]. It is a feed-forward network which can be organized onto three steps, or three layers are [8]:

A. Patch Extraction and Representation
B. The non-linear mapping
C. Image Reconstruction.

The Proposed System

The proposed system is a medical images enhancement system. It involves many stages such as preprocessing, enhancement, and post processing stages. Figure (1) illustrates the main stages of our proposed system.

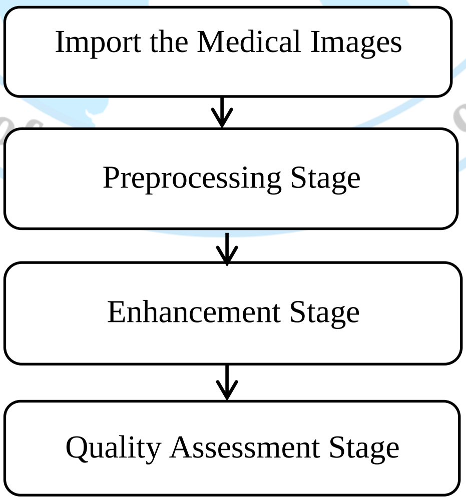

Figure 1: General block diagram of the medical image enhancement proposed system.

The proposed system is designed to work with two groups of medical images which from the utilized apparatuses such as CT scan and MRI. The proposed system for medical images enhancement is represented by three stages as shown in the Figure (2).

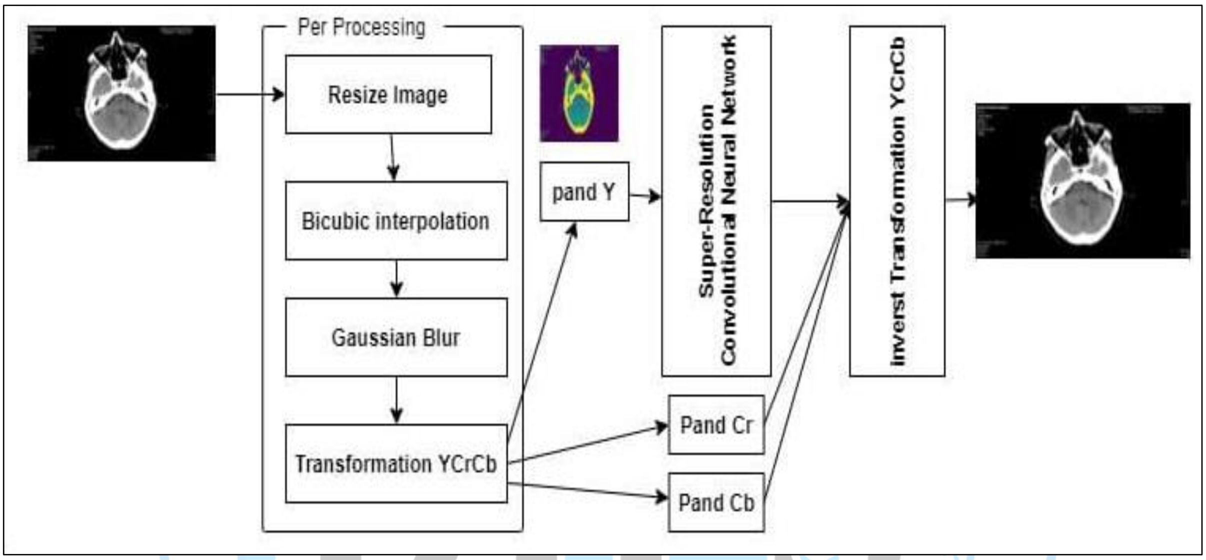

Figure 2: The Proposed System Medical Image Enhancement Layout.

A- Pre-processing Stage

The first stage in our second proposed system in the preprocessing stage. This stage aims to preparation image for the next stage, which is the enhancement stage. At this stage, many steps are implemented such resizing (image scaling up) step, and image Gaussian blurring step. The Gaussian blur for smoothen images is performed after the step of interpolation. Different sizes of filter were used such as (3×3), (7×7) and (13×13), the value of σ is conceded as 1. These sizes of filter are performed for both groups of images sources (CT and MRI).The transformation of the $YCrCb$ channel is the last step in the preprocessing stage. This stage is designed to transform the image from RGB color channel to YCrCb base on using equation(5, 6 and 7) [9]:

$$\boldsymbol{Y = R \times 0.301 + G \times 0.586 + B \times 0.113} \quad \textbf{(5)}$$

$$Cb = R \times -0.168 + G \times -0.332 + B \times 0.500 + 128 \quad (6)$$

$$Cr = R \times 0.500 + G \times -0.417 + B \times -0.082 + 128 \quad (7)$$

B- Enhancement Stage

The transformed smoothed image is enhanced using one of the most powerful image super resolution model (SRCNN). This stage produces a high-resolution (HR) medical image from a low-resolution (LR) one. In this stage, we used an implement SRCNN model as is shown in Figure (3).

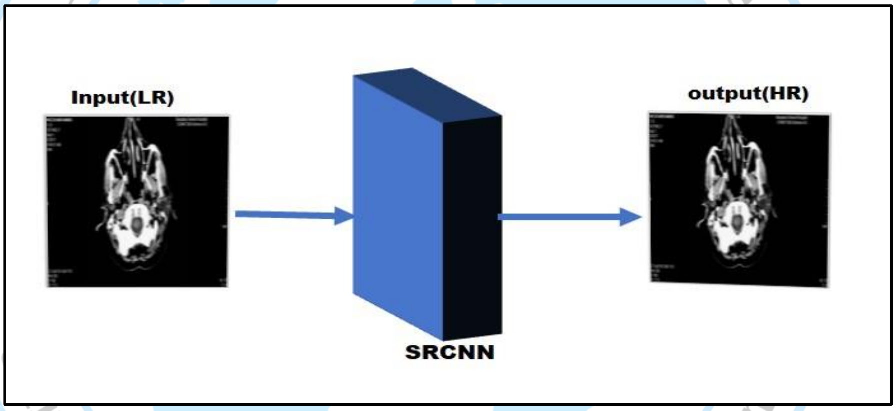

Figure 3: The SRCNN for image enhancement.

C- Post processing Stage

The last stage of our proposed system is the post processing stage. In this stage, the inverse image is converted and recovered to the original RBG color image. The transformation process in this stage is implemented based on using the equations (8, 9, and 10) [10]:

$$R = (Yx - 16) \times 1.164 + (Crx - 128) \times 1.596 \quad (8)$$

$$G = (Yx - 16) \times 1.164 - (Crx - 128) \times 0.813 - (Cbx - 128) \times 0.391 \quad (9)$$

$$B = (Yx - 16) \times 1.164 + (Cbx - 128) \times 2.081 \quad (10)$$

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Result and discussion

In this study, the dataset that is used in proposed system has 67 CT scan images and 105 images MRI are collected from the different local clinic, Results and measurements of only five samples were used in this paper. The proposed system involved another three sub stages which are conducted in our desired system. The first stage is the preprocessing stage followed by the second stage which is image enhancement stage based super resolution mechanize while the final stage is the quality assessment stage using different criterions such as Structural Similarity Index Metrics (SSIM) [11], Peak-Signal-To-Noise-Ration (PSNR) [12], Mean-Square-Error (MSE) [12], Universal Quality Index (UQI) [13], The formulas of these measures are given in equations:

$$\boldsymbol{SSIMi(t) = I_i(t).C_i(t).S_i(t)} \quad \textbf{(11)}$$

Where parameter $I_i\ (t)$ is for the luminance difference, $C_i\ (t)$ is a contrast difference and $S_i(t)$ is a Structure difference measure between blocks of the disturbed images and the original one.

$$\boldsymbol{PSNR = 10\ log\left(\frac{D^2}{MSE}\right)} \quad \textbf{(12)}$$

Where D stands for the dynamic range of pixel intensities, and MSE is the Mean squared error that refers to the power of the distortion.

$$\boldsymbol{MSE\ = \frac{1}{MN}\sum_{j-1}^{M}\sum_{i-1}^{N}(I_{ref}(i,j) - I_{tst}(i,j))^2} \quad \textbf{(13)}$$

Where M and N the size of image, $I_{ref}(i,j)$ is the original image, $I_{tst}(i,j)$ is the enhanced image.

$$\boldsymbol{UQI = L(c,s).C(c,s).S(c,s)} \quad \textbf{(14)}$$

Where $L(c,s)$ is luminance distortion, $C(c,s)$ is contrast distortion, and $S(c,s)$ structural comparisons.

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The first experimental results of our proposed system are illustrated in Figure (4). Firstly, all the medical images are smoothed using Gaussian blur filters. Different Gaussian filters are used to different medical images. The experimental results demonstrate the best outcomes that are achieved when the mask (7×7) is used on the CT scan, MRI images.

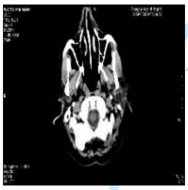
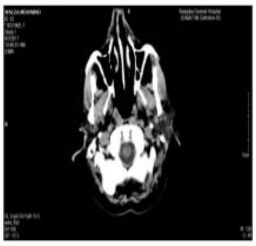
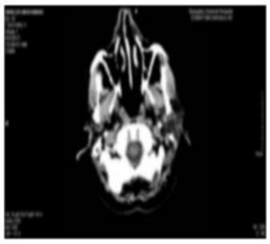
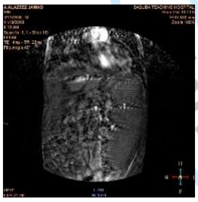
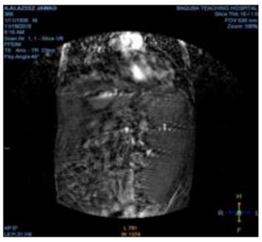
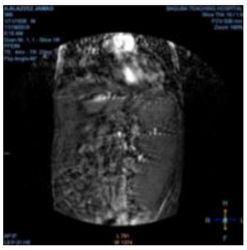
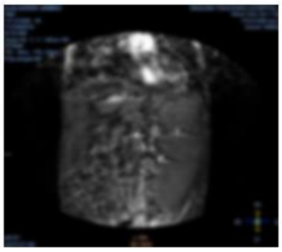
Original images CT scan	**Gaussian Mask Size**		
	3*3	**7*7**	**13*13**
			
Original images MRI	**Gaussian Mask Size**		
	3*3	**7*7**	**13*13**
			

Figure 4: Image smoothing using Gaussian blur results for CT scan, MRI images.

The second experimental results are performing after the medical images are converted from color space (RGB) to color space (YCrCb) for a CT scan, MRI images are illustrated in Figure (5).

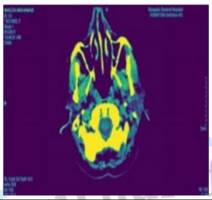
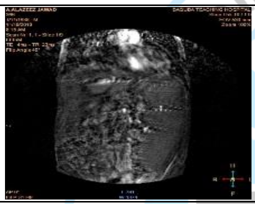
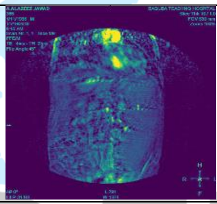
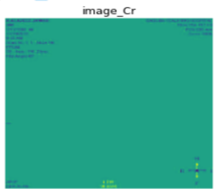
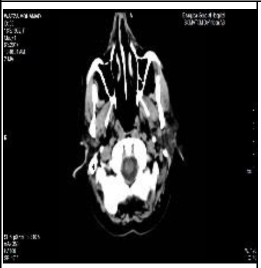
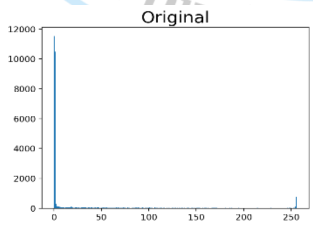
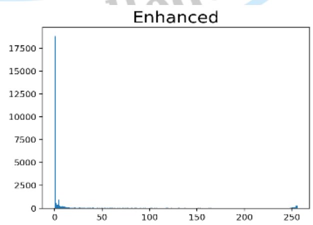
<table>
<tr><td rowspan="2">Original images CT Scan</td><td colspan="3">Transformation RGB to YCrCb</td></tr>
<tr><td>Pand Y</td><td>Pand Cr</td><td>Pand Cb</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Original images MRI</td><td colspan="3">Transformation RGB to YCrCb</td></tr>
<tr><td>Pand Y</td><td>Pand Cr</td><td>Pand Cb</td></tr>
<tr><td></td><td></td><td>
</td><td>
</td></tr>
</table>

Figure 5: Transformation Results for CT scan, MRI images

The third experimental results of the medical enhancement proposed system are illustrated in Figure (6). The enhanced medical images are obtained from the Super Resolution convolutional Neural Network (SRCNN) model as well as the image histograms before and after the processing stage using a CT scan, MRI images.

<table>
<tr><td colspan="4">CT Scan Images</td></tr>
<tr><td colspan="2">Histogram Original images</td><td colspan="2">Histogram Enhanced images</td></tr>
<tr><td></td><td>
</td><td>
</td><td></td></tr>
<tr><td colspan="4">MRI images</td></tr>
<tr><td colspan="2">Histogram Original images</td><td colspan="2">Histogram Enhanced images</td></tr>
</table>

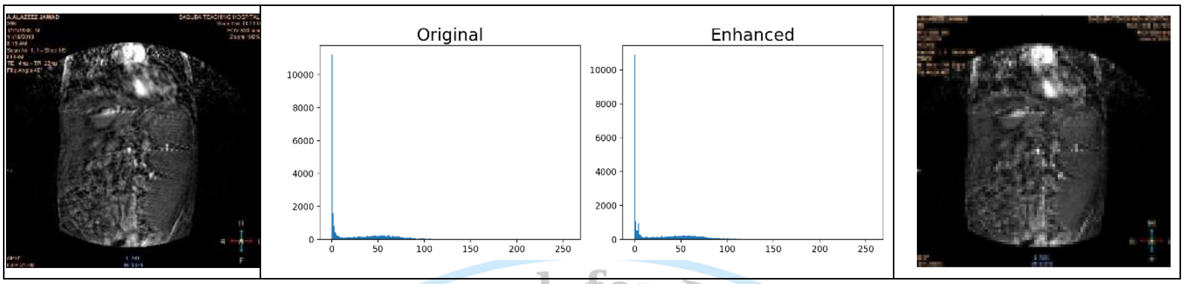


Figure 6: SRCNN Results for MRI images.

Image Enhancement Quality Assessment

The experimental results of our proposed system are evaluated based on using the original medical images and the smoothed ones with the super resolution model (SRCNN). The experimental results show that the smoothed medical image using Gaussian blur is better than the without Gaussian blur.

CT scan Images

Tables (1), illustrates the quality assessment of the five CT scan images. We notice that the PSNR, SSIM and UQI are increased after enhancing the medical images using our proposed system with image smoothing based Gaussian mask while the MSE is decreased.

Table 1: Quality Metrics for CT scan Images.

	Image Id	Images without Gaussian blur				Images with Gaussian blur			
		SSIM	**PSNR**	**MSE**	**UQI**	**SSIM**	**PSNR**	**MSE**	**UQI**
CT Scan	CT_Im1	0.842	23.042	322.742	0.594	0.891	30.768	54.483	0.630
	CT_Im2	0.886	25.668	176.28	0.799	0.950	38.697	8.776	0.828
	CT_Im3	0.875	25.677	175.908	0.898	0.942	34.711	21.977	0.929
	CT_Im4	0.912	25.971	164.403	0.873	0.961	38.514	9.154	0.913
	CT_Im5	0.845	24.215	246.322	0.853	0.916	31.295	48.256	0.893

Figures (7) illustrates the SSIM, PSNR, MSE and UQI metric of the medical image enhancement using our proposed system for five CT scan images. The Figures show that, the SSIM, PSNR and UQI When using smoothed images which are increasing (that is represented in red line) In the other hand, SSIM, PSNR and UQI of the images without Gaussian mask are decreasing (that is represented in blue line). The MSE values are decreasing when the smoothed images are used (that is represented in red line) while the MSE of the images without a Gaussian mask are increasing (that is represented in blue line).

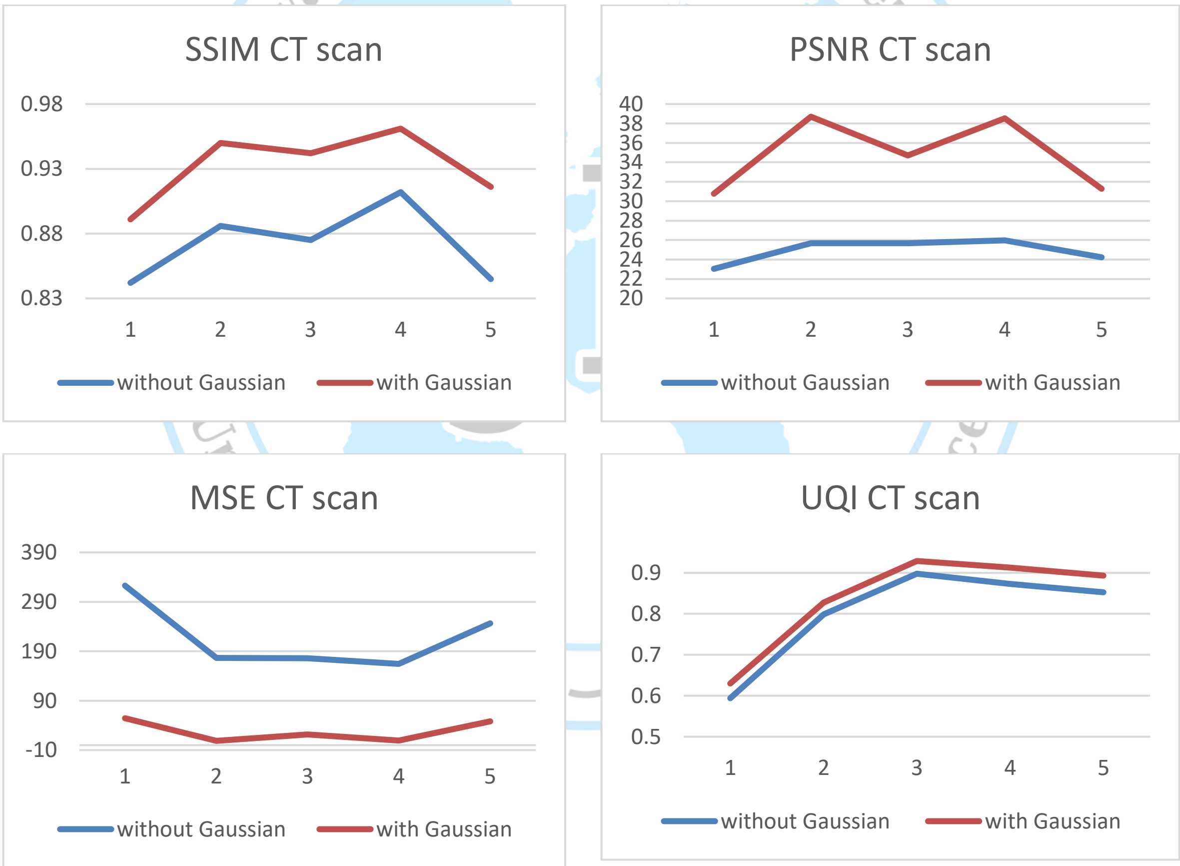


Figure 7: SSIM, PSNR, MSE, and UQI for CT scan images.

Tables (2), illustrates the quality assessment of the five MRI images. The PSNR, SSIM and UQI are increased after enhancing the medical images using proposed system with image smoothing based Gaussian mask while the MSE is decreased.

Table 2: Quality Metrics for MRI Images.

	Image Id	Images without Gaussian blur				Images with Gaussian blur			
		SSIM	**PSNR**	**MSE**	**UQI**	**SSIM**	**PSNR**	**MSE**	**UQI**
MRI	MRI_Im1	0.867	25.430	186.211	0.795	0.948	38.690	8.791	0.831
	MRI_Im2	0.886	25.668	176.282	0.799	0.950	38.697	8.776	0.828
	MRI_Im3	0.875	25.677	175.908	0.898	0.942	34.711	21.977	0.929
	MRI_Im4	0.912	25.971	164.403	0.873	0.961	38.5143	9.154	0.913
	MRI_Im5	0.845	24.215	246.322	0.853	0.916	31.295	48.256	0.893

Figures (8) illustrates the SSIM, PSNR, MSE and UQI metric of the medical image enhancement using our proposed system for five MRI images. The figures show that the SSIM, PSNR and UQI when using smoothed images are increasing (that is represented in red line) in other hand, the SSIM, PSNR and UQI of the images without a Gaussian mask are decreasing (that is represented in blue line). The MSE values are decreasing when the smoothed images are used (that is represented in red line) while the MSE of the images without a Gaussian mask are increasing (that is represented in blue line).

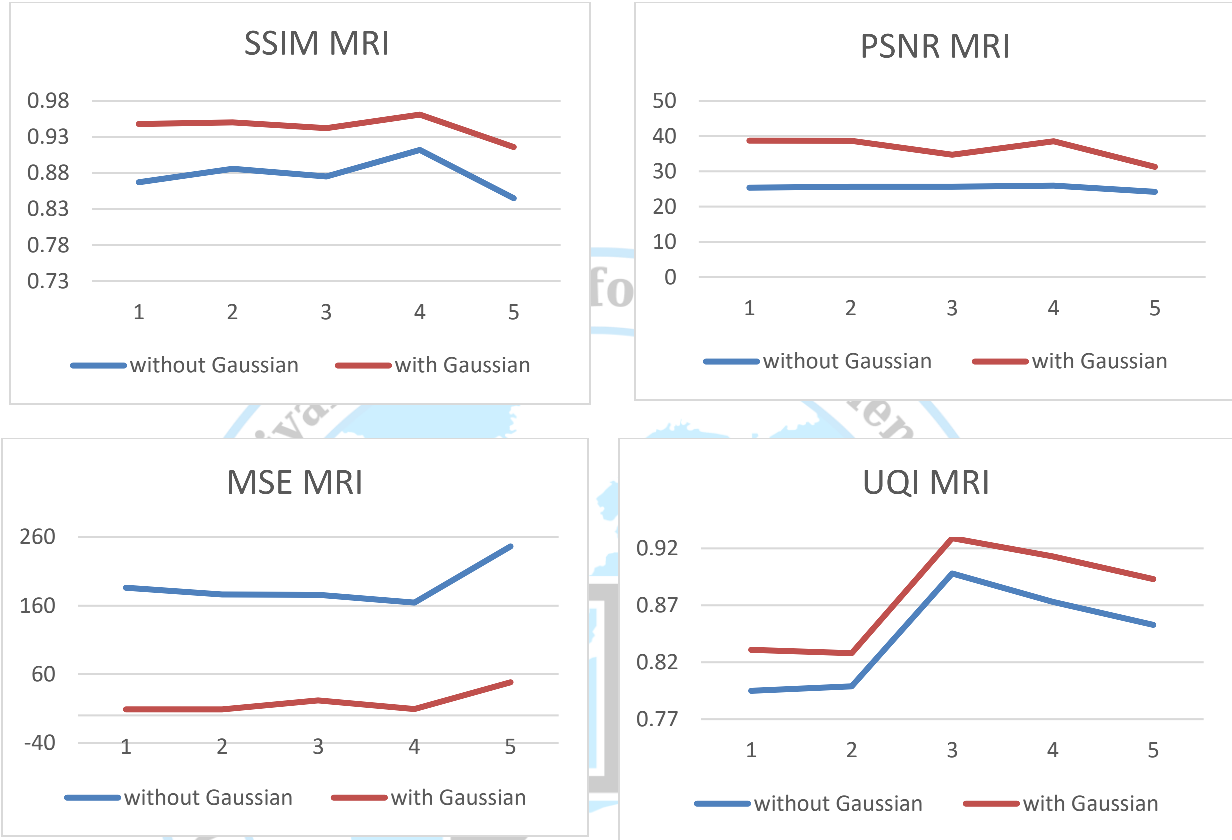


Figure 8: SSIM, PSNR, MSE, and UQI for MRI images.

Conclusion

Some medical instrument՝s imaging systems that are used in operating theater hospital have some technical issues such as hardware and software. Those issues affect the outcome of the medical files such as videos and images. Some reasons of that are: the type and quality of the imagining device itself, accuracy, and efficiency of the imaging system of the device are all reasons for causes some problems of the operation outcome (images). Some technical issues such as the absorption of part of the ray’s energy by tissues, blood, and gas particles caused poor image quality and inaccuracy. To overcome of these issues, there are two possible options. The first one is developed and enhance the hardware of the imaging system which cost a lot of money and it is time consuming. Other, is to design and implement a software that can enhance the outcome of those devices. In this paper, we solve the imaging systems issues by proposing software's for the medical image's enhancement. In other words, solving this issue can achieve the following: the proposed system for processing medical images for two imaging devices, CT-scan and MRI is good in terms of quantitative measurements, but the human eye did not notice a difference between the two images because the change is simple in the image. The use of a high-resolution convolutional neural network to enhancement images helps to detect tumors in early stages, and therefore the proposed system will help save human life.

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