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Research Article

Efficient Colorization of Medical Imaging based on Colour Transfer Method

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Abstract: Colorization is an automatic technique to enhance greyscale images by introducing chromatic information. In this research we investigate to produce colorized medical images, potentially supporting in better understanding of anatomy, anomalies and infections. Begins with proposed mandatory preprocessing steps for medical images noise removal and edge improvement, followed by colorization process. On providing target color reference medical image, chromatic information was transferred to greyscale input image. The generated colorized medical images are excellent representation biomedical structures. Performance of the proposed technique was compared with state of art methodologies, yet evaluation parameters validate the supremacy of proposed system.

Keywords: Image processing, colorization of medical images, bioinformatics, medical images enhancement.

1. INTRODUCTION

Human visual system visually differentiates between different material on the bases of colors and structures. On application of digital image processing techniques color attribute supports in understanding of medical images. The proposed colorization algorithm enhances the hidden information treasured in greyscale medical images.

Information signal in medical images is highly sensitive with Gaussian and salt and pepper noise. Mostly medical image modality are higher in contrast and intensity as compared to natural every day images [1]. Colorization algorithm reported for natural images were failed to produce colour medical image [1-15].

The main intuition for our contribution was to construct a utility to remove any type of noise and enhance the medical images on application of colorization algorithm. The framework consists of pre-processing phase followed by colorization phase. A generic pre-processing phase was recommended before apply any colorization algorithm on medical images. Thus, proposed methodology recommends all medical modality pre-processed by proposed enhancement steps before application of any colorization technique.

1.1 Literature Review

Colorization of greyscale natural images is research area under consideration of researchers since a decade. Whereas, there are only few research findings in colorization of medical images. There is a need to identify efficient algorithms to play their part in building colorization mechanism for medical image.

Colorization algorithms can be categorize into three main groups namely, automatic, semi-automatic and user coloring techniques [2]. Recent colorization technique used seeded pixel to propagate colour to similar texture

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neighbouring pixel [3].

The foundation concept of colorization was laid by Welsh in 2002 using a semi-automatic colouring of natural images.L α β colour space was used to colorized natural images. Same technique have shown poor quality results when applied on medical images [4]. Another study demonstrates to introduce false colouring to colorized CT images. Resources consumption and processing time was higher [5-7]. Another study examine a methodology to colorize MRI images by comparing luminance between the two images [8]. Fusing three types of medical modality of same region of interest produces a colorized medical image [9,10]. Moreover, using probability estimations based on prior information to compute possible chromatic information [11]. Similarly, another colorization technique used pseudo random cypher to generate colorized images [12]. To estimate the possible colour code texture information was used [13]. Further, video colorization technique to colorize key frame is based on a small number of colour seed and propagate chrominance to remain pixels. Eventually, remaining similar frames were colorized using generated colorized key frame as reference image [14, 15].

The proposed algorithm is extension of our past work in which we colorize medical images and standardize quality parameter to validate the performance of any colorization algorithm. Structural similarity index, peak signal to noise ratio, measure of enhancement and entropy was used to measure resulting colorized output [16].

1.2 Contributions

Following are the major innovative contributing in academic research in biomedical diagnosis in medical modality colorization, studying human biological phenomena and anatomy. Diagnosis of disease and construction simulation for blood flow within human body.

2. MATERIALS AND METHODS

The proposed framework colorized medical images in two steps. Initially, preprocessed the input greyscale image and later colorized the medical image illustrated in Fig. 1. Contrast, luminance and structural details were enhanced in preprocessing step. Finally, colorization step was applied to introduce chromatic information.

2.1 Medical Image Enhancement Step

Black and white medical images were preprocessed, to improve the visual details within the image. None of the report study discusses any preprocessing for colorization. Significantly, this pre-processing contributes in good visual representation, thus promising resulting colorized images were generated.

Open source medical imaging dataset was used to test the performance proposed system. Resolution of images were adjusted by 256x256 pixels. Weighted averaging filter was used to remove noise signals. Let weighted kernel convolve with entire image to remove noise shown in expression (1-2).

$$\text{Weighted Filter} = 12\text{P5} - \sum_1^4 \text{Pi} + \sum_6^9 \text{Pi} \quad (1)$$

$$\text{I(x, y)} = \text{I(x, y)} * \text{Weighted Filter 2)}$$

The intensity of image pixels were equalizes to normalize and improve the contrast of luminance of input greyscale source image illustrated in (4), I(x,y) represents transform intensity, summation of Zipixel intensity under processing divided by total number of pixel.

$$\text{I(x, y)} = \sum_{i=0}^{n} \frac{\text{Zi}}{\text{total pixel}} \quad (4)$$

After contrast enhancement input image was convolve with sobel edge detector to improve edge information. Mathematical expression (5-6) depicts sobel operation.

$$\text{Ix} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * \text{Ix, y} \quad (5)$$

$$\text{Iy} = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * \text{Ix, y} \quad (6)$$

Improved edge information helps in better defining texture of medical structures. Image

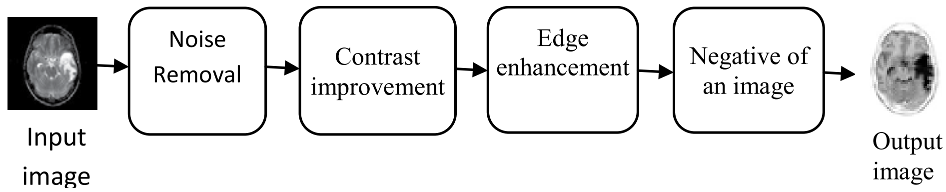


Fig. 1. Preprocessing steps of proposed methodology.

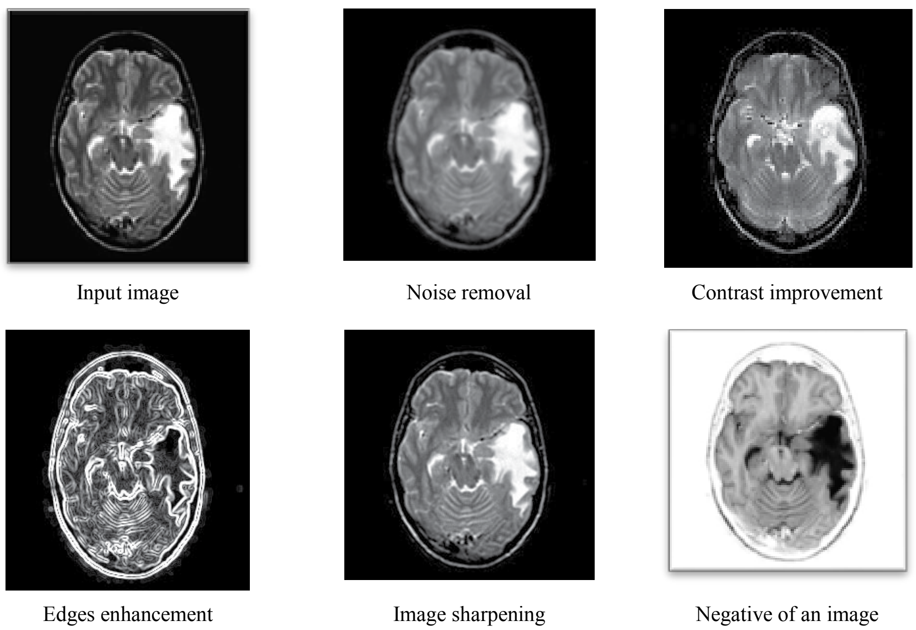


Fig. 2. Pre-processing phase output images of each step.

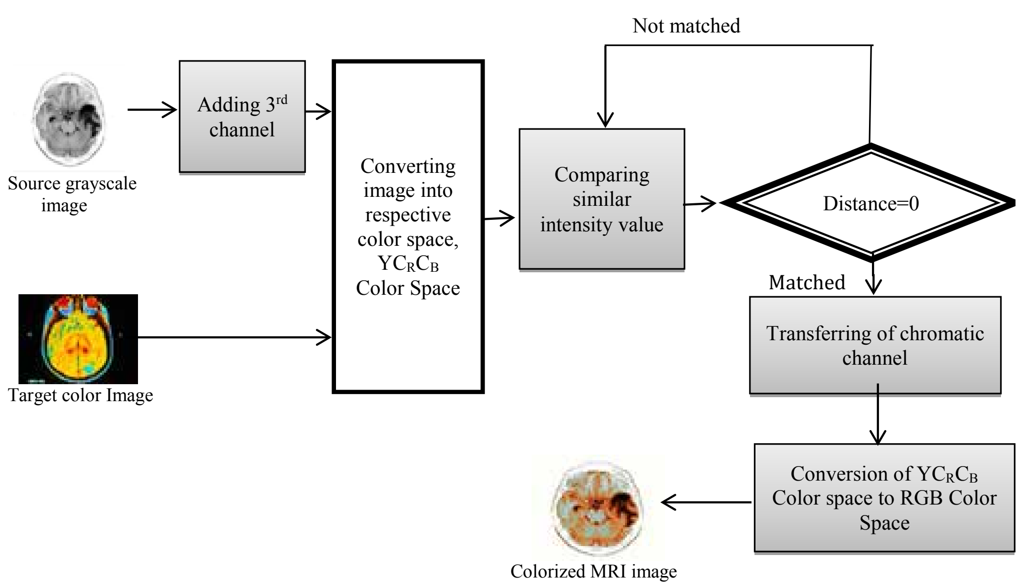


Fig. 3. Flow chart of colorization phase.

Table 1. Datasets for experimental evaluation.

	Medical Modality	Dataset Description & Source	Number of Images
1	**CT**	The test samples images of normal brain, bladder, heart, kidneys and liver were used for experimental validation of framework [19]	10
2	**Mammogram**	This dataset includes data from a random sample of 10 digital mammograms received from women of age 60-89 years by National Cancer Institute-funded Breast Cancer Surveillance Consortium [20]	10
3	**MRI**	The dataset includes MRI of normal eye, brain tumor, heart, knee and spine [21]	10
4	**Nuclear Medicine**	The dataset includes nuclear medicine images of two lower abdomens, complete body, foot and spine [22]	10
5	**PET**	The dataset includes PET images of two lower abdomens, heart and brain [19]	10
6	**Ultrasound**	Ten 2D ultrasound sequences of the liver of healthy volunteers were acquired during free breathing over a period of 5-10 min. Dataset is open source used in research study [19]	10
7	**X-ray**	Open source dataset of X-ray modality was used [23]	10

gradient and phase information was calculated to record the orientation of edges (7-8).

$$\mathrm{I(x,y)} = \sqrt{\mathrm{Ix}^2 + \mathrm{Iy}^2} \tag{7}$$

$$\emptyset = \tan^{-1}\frac{\mathrm{Iy}}{\mathrm{Ix}} \tag{8}$$

Image was further pre-processed and each pixel intensity was subtracted from maximum intensity of image. Expression 9 representing maximum intensity of image m subtracted from p intensity of pixel under processing

$$\mathrm{I(x,y)} = \mathrm{m} - \mathrm{p} \tag{9}$$

The output generated by each step of pre-processing represented in Fig. 2. After processing through pre-processing phase processed image was input in colorization phase.

2.2 Medical Image Colorization Step

After preprocessing resulting output was inserted in colorization step as input. Flow chart represented in Fig 3 shows the series of processes to colorize medical images. Input source grayscale preprocessed image was two dimension image and a third channel was created initially populated by ones. This channel was later used to hold chromatic information. Both source and target reference image was normalized within the define intensity range 10.

$$\mathrm{I(x,y)} = \frac{\mathrm{Intemsity(pixel)\times 255}}{255-\left(\begin{matrix}\text{maximum Intensity(x,y)}-\\ \text{minimum Intensity(x,y)}\end{matrix}\right)} \tag{10}$$

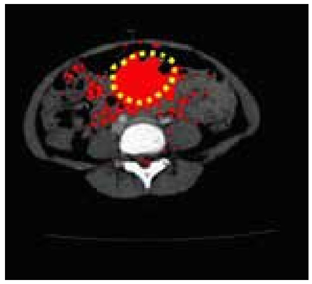
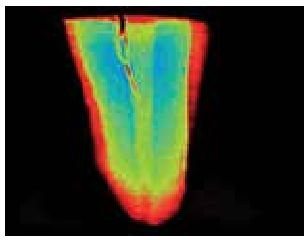
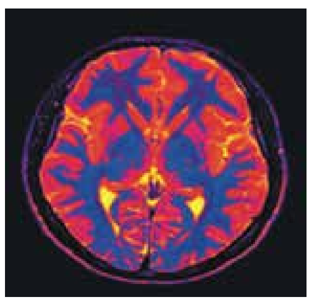
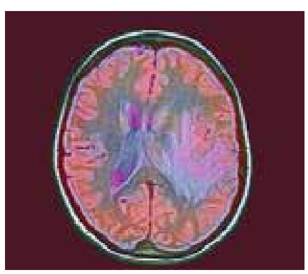
Target reference image and greyscale source image color space was converted from RGB and greyscale YC_bC_r color space. , making both the images compatible to each other. Intensity of both images were compared using Y channel. On finding the similar intensity chromatic value of target image pixel was transferred to source image and store in third channel. Entire source image was mapped with chromatic value. Finally, source image was converted to RGB to visualize the produce colorized medical image.

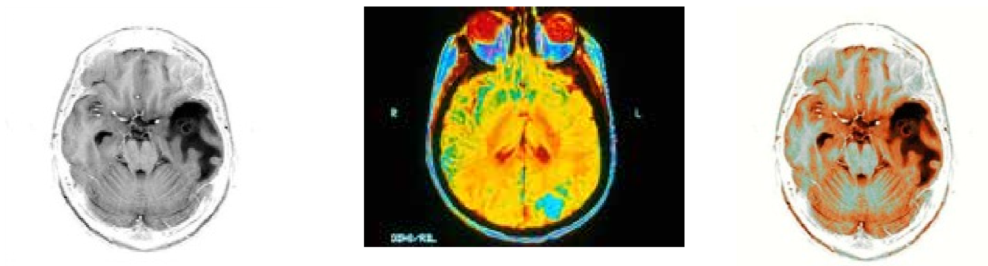
3. RESULTS

3.1 Dataset

Sample test images obtained from various open source medical images datasets repository were used for experimental evaluation of proposed framework [15-19]. Following Table 1 describes the open source dataset and number of test samples.

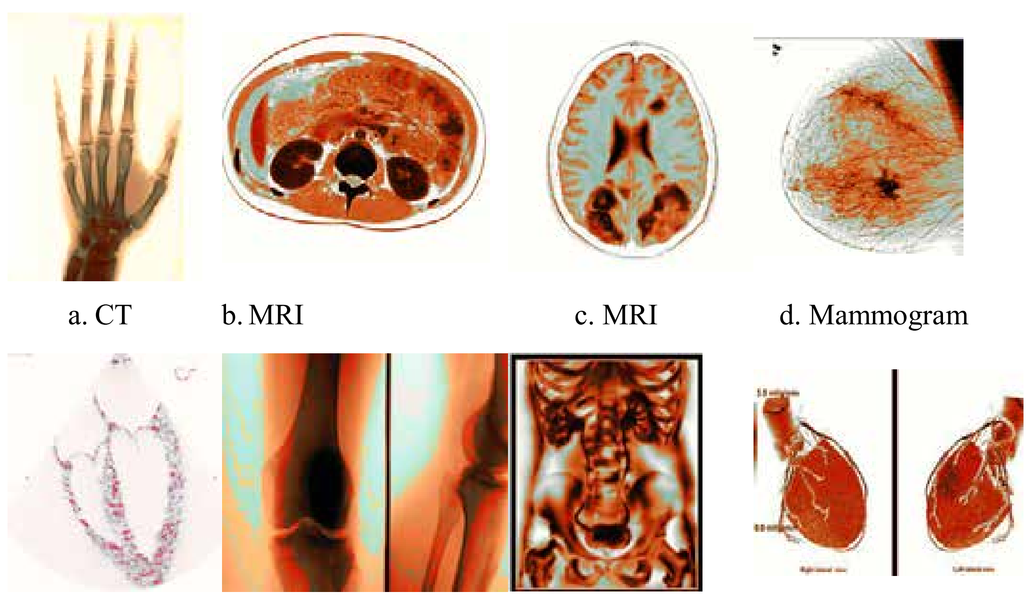
Table 2. Comparative analysis of colorization of medical imaginary of recent studies with proposed framework.

	Methodology	Resulting Image	Limitations	Advantages
1.	Pseudo colorization by assigning value to pixel based on tissue density RGB color map[5].		A limited set of colors to be displayed.	Tumor area detection
2.	Pseudo colorization[7].		A limited set of colors to be displayed.	Tooth fracture detection
3.	Based on color transferring method. Clustering homogenous intensity pixel to separate tissues[8].		A limited set of colors to be displayed.	Brain tissues detection.
4.	Image Fusion along with fast discrete curvelet transform[9].		Merge three types of images T1,T2 and PD weighted.	Diagnosis.
5.	Proposed framework utilizes methodology of chromatic value transfer between medical images.			To analyze the anatomy of the human being, diagnosis of various diseases. Identification of tissues, cells, and organs. Diagnosis of brain tumor, breast cancer, internal organ bleeding, bone fractures, etc.



(a) Input source greyscale image **(b). target reference color image** **(c). Output Colorized Image**

Fig. 4. Colorization output of medical imaging.



a. CT b. MRI c. MRI d. Mammogram

e. Ultrasound f. Xray e. Nuclear medicine f. PET

Fig. 5. Colorized outcomes of proposed colorization methodology at different medical modality.

3.2 Results

The proposed algorithm gave significantly better visual description of subjected greyscale medical image. On closer examination, the resulting colorized medical image produces a meaningful perception.Colorized outcomes of proposed colorization methodology on different medical modality represented in 5. The strength of proposed system was that it can colorized any type of medical image such as, CT, MRI, mammogram, ultrasound, XRAY images, etc.

3.3 Comparison with State of the Art Methodologies

A comparison of generated output by various reported colorization algorithms along with the limitation of report study were elaborated in Table 2. Colorization by transferring by example was reported to colorize natural images but similar study fails to colorize medical images [4].

4. DISCUSSION

Visually improved medical images play a vital role in diagnosis. Identification of internal anomalies, fractures and bleeding at initial stages will support in better treatment of patient and potentially contributes in increasing the survival rate.

The procedure of assignment of chromatic value to the second and third channels of source medical image is demonstrated in Fig. 6. To understand this point, the processing pixels value of three channels i.e., a window of 5×5 at location (88, 55) was chosen. The source pixel at location (88, 55) was compared with target color image pixels (88, 55) within 5×5 neighborhood and the best candidate is selected that holds the similar intensity value. Since both the source and target images hold the same intensity value 234 at location (88, 55), chromatic value 128 and 125 of the target image at (88, 55) was assigned to the source image. Similarly, another source pixel at location (88, 59) was compared with target color image pixels (92, 55) and the best candidate is chosen that holds similar intensity value 62. So, chromatic values 79 and 180 of the target image at (92, 55) was assigned to the source image in C_bC_r channel. In a similar context, this point processing scans the entire image. On similar intensity value, the chromatic value of C_bC_r of the target color medical image was transferred to all pixels of the source image.

Quality assurance parameters for colorization of medical images discussed in our previous research was used to compare the performance of state of the art techniques [16]. Two quality measures peak signal to noise ratio PSNR and structural similarity index SSIM were used to record the enhancement in appearance of generated colorized image Fig. 7. Higher the value of PSNR represent good image quality and better visual information[16,17]. The average PSNR value of ten colorized images of each modality was within the range of 58~75. Likewise, SSIM estimates the structural and luminance similarity measure between input and output images. Greater luminance and structural similar images have SSIM value 1 [18]. The average SSIM value of ten colorized images of each modality was within 0.8~1. Thus, proposed framework contributed in enhancing medical images perception and overall improvement of its quality as well.

To justify the credibility of proposed system image quality of resulting colorized images were examined. Significantly computed image quality parameters were recorded from colorized images. The resulting colorized images produce by proposed framework validates a dramatic enhancement and emphasizes minor details hidden within greyscale monotonic medical images. Potentially, it supports in real time diagnosis that leads to faster diagnosis and overall improve patient's care as well as survival rate.

4. CONCLUSIONS

In this paper, automatic medical image colorization algorithm was proposed, helps in image enhancement as well as discrimination between different types of organs, tissues, and cells. This method helped to reduce the burden of medical professional in accurate diagnosis. In future, researchers can work to form comprehensive clinical decision support system

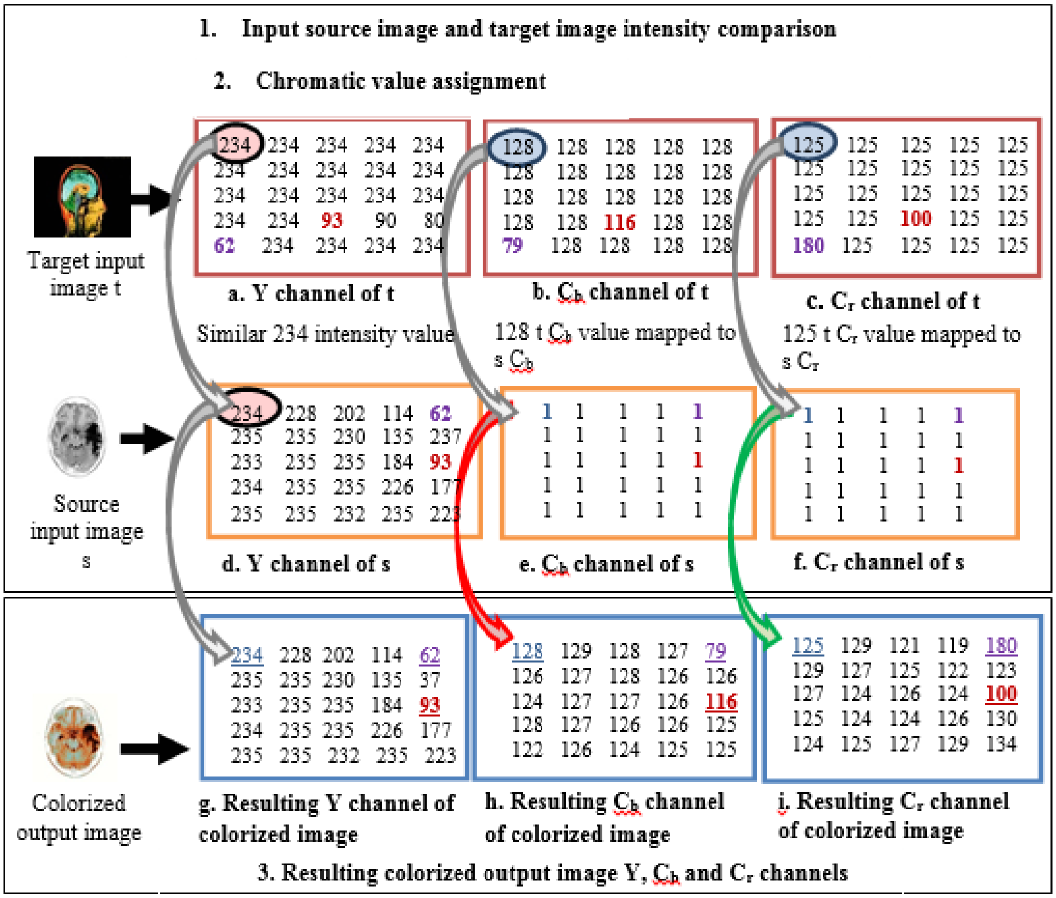


Fig. 6. Chromatic channel transferred between source image s and target image t in a 5×5 window display at location (88, 55). Point processing between s and t images 1.a. Source image pixel intensity value of Y channel was compared with all the pixels of target image t at location 2. The chromatic value was assigned to similar intensity pixels of s and t 3. Resulting pixels value of colorized output image.

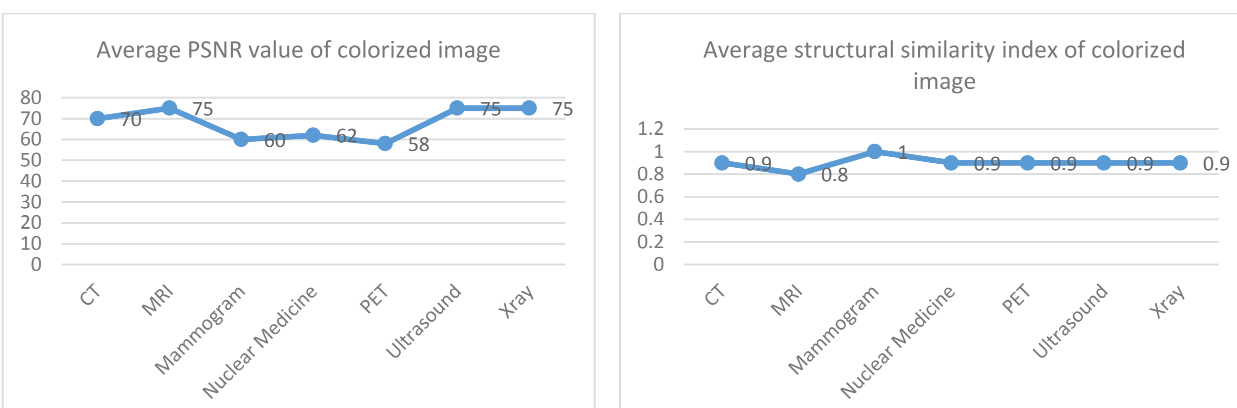


Fig. 7. PSNR and SSIM analysis of generated colorized medical imaging

using colorized medical images for diagnosis. Colorization of medical images support the doctors in the precise diagnosis of abnormalities.

6. REFERENCES

1. Shinde, B., D. Mhaske, & A. R. Dani. Study of noise detection and noise removal techniques in medical images. *International Journal of Image, Graphics and Signal Processing* 4(2): 51-60 (2012).
2. Popowicz, A. & B. Smolka. Overview of grayscale image colorization techniques. In: *Color Image and Video Enhancement*. Springer, p. 345-370 (2015).
3. Celeste, N.L.U.,& J.P.T. Yusiong. Grayscale Image Colorization using Seeded Cellular Automaton. *International Journal of Advanced Research in Computer Science* 6: 242-249 (2015).
4. Welsh, T., M. Ashikhmin, & K. Mueller. Transferring color to greyscale images. *ACM Transactions on Graphics (TOG)* 21: 277-280 (2002).
5. Martinez-Escobar, M., J. L. Foo, & E. Winer. Colorization of CT images to improve tissue contrast for tumor segmentation. *Computers in Biology and Medicine* 42: 1170-1178 (2012).
6. Li, F., L. Zhu, L. Zhang, Y. Liu, & A. Wang. Pseudo-colorization of medical images based on two-stage transfer model. *Chinese Journal of Stereology and Image Analysis* 2: 8-15 (2013).
7. Tofangchiha, M., M.Bakhshi, M. Shariati, S. Valizadeh, M. Adel, & F. Sobouti. Detection of vertical root fractures using digitally enhanced images: Reverse-contrast and colorization. *Dental Traumatology* 28: 478-482 (2012).
8. Attique, M., G. Gilanie, M.S. Mehmood, M.S. Naweed, M. Ikram, J.A. Kamran, & A. Vitkin. Colorization and automated segmentation of human T2 MR brain images for characterization of soft tissues. *PLoS ONE* 7: 33-39 (2012).
9. Giesel, F.L., A. Mehndiratta, J. Locklin, M.J. McAuliffe, S. White, P.L. Choyke, M.V. Knopp, B.J. Wood, U. Haberkorn, & H. von. Tengg-Kobligk. Image fusion using CT, MRI and PET for treatment planning, navigation and follow up in percutaneous RFA. *Experimental Oncology* 31: 106-112 (2009).
10. Kumar, Y.K. Comparison of fusion techniques applied to preclinical images: fast discrete curvelet transform using wrapping technique & wavelet transform. *Journal of Theoretical and Applied Information Technology* 5: 668-673 (2009).
11. Noda, H., J. Korekuni, & M.A Niimi. colorization algorithm based on local MAP estimation. *Pattern Recognition* 39: 2212-2217 (2006).
12. Ko, K.-W., I.-S. Jang, W.-J. Kyung, & Y.-H. Ha. Saturation compensating method by embedding pseudo-random code in wavelet packet based colorization. *Journal of the Institute of Electronics Engineers of Korea SP* 47: 20-27 (2010).
13. Lipowezky, U. Grayscale aerial and space image colorization using texture classification. *Pattern Recognition Letters* 27: 275-286 (2006).
14. Horiuchi, T. Colorization algorithm using probabilistic relaxation. *Image and Vision Computing* 22: 197-202 (2004).
15. Khan, T.H., S.K., Mohammed,M.S. Imtiaz, & K.A.Wahid. Efficient color reproduction algorithm for endoscopic images based on dynamic color map. *Journal of Medical and Biological Engineering* 36: 226-235 (2016).
16. Nudrat, N. M. Sharif,M.U.G. Khan, Y. Mussarat, & S. L. Fernandes. A framework for automatic colorization of medical imaging. The IIOAB Journal 7: 202-209 (2016).
17. Agaian, S.S., K. Panetta, & A.M.Grigoryan. Transform-based image enhancement algorithms with performance measure. *Image Processing, IEEE Transactions on Image Processing* 10: 367-382 (2001).
18. Wang, Z., A.C. Bovik, H.R. Sheikh, &E.P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *Image Processing, IEEE Transactions on Image Processing* 13: 600-612 (2004).
19. Rosset, A., L. Spadola, & O.Ratib. OsiriX: an open-source software for navigating in multidimensional DICOM images. *Journal of digital imaging* 17: 205-216 (2004).
20. Clark, K., B. Vendt, K. Smith, J. Freymann, J. Kirby, P. Koppel, S. Moore, S. Phillips, D. Maffitt, M. Pringle, & L.Tarbox. The cancer imaging archive (TCIA): maintaining and operating a public information repository. *Journal of Digital Imaging* 26: 1045-1057 (2013).
21. Sutton, D. The whole brain atlas. BMJ 319:1507-1523 (1999).
22. Hutton, B.F., M. Braun, L. Thurfjell, & D.Y. Lau. Image registration: an essential tool for nuclear medicine. *European Journal of Nuclear Medicine and Molecular Imaging* 29: 559-577 (2002).
23. Shiraishi, J., S. Katsuragawa, J. Ikezoe, T.Matsumoto, T. Kobayashi, K.I.Komatsu, M.Matsui, H. Fujita, Y. Kodera, & K. Doi. Development of a digital image database for chest radiographs with and without a lung nodule: receiver operating characteristic analysis of radiologists' detection of pulmonary nodules. *American Journal of Roentgenology* 174: 71-74 (2000).