

A COLOR PRE-PROCESSING METHOD FOR TUMOR SEGMENTATION USING HUMAN LIVER CT IMAGES

Abid Farooq¹, Aqsa Khursheed², Hina Shafique³, Shafqat Ali⁴, Ghulam Gilanie⁵

^{1,2,3,5}Department of Artificial Intelligence, Faculty of Computing, The Islamia University of Bahawalpur, Pakistan.

⁴Department of Mathematics, Faculty of Physical and Mathematical Sciences, The Islamia University of Bahawalpur, Pakistan.

¹abid.farooq12@gmail.com, ²aqsakhursheedbwp@gmail.com, ³hinach1912@gmail.com, ⁴shafqat.ali@iub.edu.pk, ⁵ghulam.gilanie@iub.edu.pk

DOI: <https://doi.org/10.5281/zenodo.21066226>

Keywords

Tumor Segmentation, Liver CT Images, interactive color pre-processing

Article History

Received: 25 April 2026

Accepted: 04 June 2026

Published: 21 June 2026

Copyright @Author

Corresponding Author: *

Ghulam Gilanie

Abstract

Segmentation is the process used to subdivide an image into its constituent regions or objects. Segmentation of structure in medical images is an important research topic. It has applications in patient diagnoses, image-guided surgery, and medical data visualization. Several segmentation methods have been reported with their own pros and cons. Some of the segmentation methods are assisted with preprocessing, such as their color representation. In this research work, a novel technique has been proposed as a preprocessing approach to color the Computed Tomography (CT) Liver images. The interactive-colored representation of CT Liver images enables the segmentation of tumorous regions present inside the slices. The proposed method has been implemented in both fully automated and semi-automated ways. A fully automated way is purely based on the Electromagnetic (EM) spectrum to color the gray information into colored one, while a semi-automated way uses the colors selected by the operator for different anatomical regions of the same human anatomy. Soft tissue mass evaluation that ranges from non-neoplastic conditions to benign and malignant tumors is a common problem, referred to as radiological findings. It is observed that these findings reliably distinguish between benign and malignant soft tissue lesions. Even expected to provide confirmatory information about the presence of a mass in preparation for possible treatment. This is due to visually evaluated radiological images, a nonstandard approach. To overcome this unreliable situation, we decided to analyze the outcome of various approaches in terms of soft tissue tumor segmentation and classification adopted by various researchers, and to provide a better solution to the highlighted problem. During our research work, we will use human liver CT images in their original. Before segmenting the pathological tissue region from healthy various colorization techniques will be analyzed to fill with appropriate colors.

1 Introduction

In the age of inventions, electromagnetic signals, transmitted by human anatomies, listen to through emerging medical imaging modalities are systematized to embody images. These modalities include X-Ray, Ultrasonography,

Computed Tomography (CT), Magneto Encephalo Graphy (MEG), Electro Encephalo Graphy (EEG), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), and MRI. This medical imagery data is then visually inspected for the

evaluation of subjects and enables the clinician to study or prepare their treatment planning. The targeted anatomical structures include the liver, prostate, kidney, heart, breasts, and abdominal structures [1, 2]. The spleen and the intestine are among the most important abdominal structures [3, 4]. More accurate and definitive radiological assessment has become decisive for the subject's therapy, such as surgery, radiation, and chemotherapy. Therefore, visualization of this medical data, holding information of biological tissues for the evaluation and assessment, is now one of the key issues of radiology departments in routine health care environments [5-20].

CT is a non-invasive medical examination with more contrast among the soft tissues and high spatial resolution. The image quality and sensitivity of CT scanners made this modality, the best, to evaluate liver abnormalities. Liver disorders are complex; therefore, radiologists are assisted through better visualization of anatomical structures for accurate and definitive diagnostic procedures. CT delivers important information about shape, size, and localization of soft tissues without revealing the subject to high ionization radiation [21, 22]. Therefore, it has central position in liver tissues evaluation process in clinical atmosphere. In routine healthcare units, a number of MRI sequences are embodied [23]. These sequences include T1 weighted (T1w), T1 with post contrast (T1C), T2 weighted (T2w), Proton Density weighted (PDw) and Fluid Attenuated Inversion Recovery (FLAIR) [24] with direct views of the body in almost any orientation i.e. coronal, sagittal and axial [25]. These sequences enable tissues to be visualized well. T1C shows better anatomical details and better distinction between solid and cystic structures while PDw shows pathological changes in better way [26]. Although, liver is protected by thick bones of skull, however, it is susceptible to many types of damage and diseases. The most common are neoplastic diseases, degenerative diseases, cerebrovascular diseases, inflammatory diseases, which can be diagnosed through CT scanners [27]. However,

if following issues are addressed at manufacturing level by CT machines vendors, fully automate diagnostic procedures be facilitated in well [28-43].

CT is short for Computed Tomography. It is a procedure used in hospitals to scan patients and determine the severity of certain diseases [44-62]. A CT machine uses an X-ray to create detailed images of the human body. CT is widely used to analyze soft tissues of human anatomical structures. Because of the image quality and sensitivity, CT is currently the best test to evaluate any abnormalities or disorders within human anatomy. The number of disorders can be quite extensive and/or complex and must be visualized well to enable the radiologist to make an accurate and definitive diagnosis. The diagnosis can be further correlated with the patient's symptoms to determine the treatment [63-80]. It is a non-invasive medical examination that helps physicians in diagnosing and treating medical conditions [81].

CT scan combines a series of X-ray images taken from different angles and uses computer processing to create cross-sectional images, or slices, of the bones, blood vessels and soft tissues inside our body. CT scan images provide more detailed information than plain X-rays do.

CT scans are special X-ray tests that produce cross-sectional images of the body using X-rays and a computer. CT scans are also referred to as computerized axial tomography. CT was developed independently by a British engineer named Sir Godfrey Hounsfield and Dr. Alan Cormack. It has become a mainstay for diagnosing medical diseases. For their work, Hounsfield and Cormack were jointly awarded the Nobel Prize in 1979.

CT scanners first began to be installed in 1974. CT scanners have vastly improved patient comfort because a scan can be done quickly [82-87]. Improvements have led to higher-resolution images, which assist the doctor in making a diagnosis. For example, the CT scan can help doctors to visualize small nodules or tumors, which they cannot see with a plain film X-ray.



Figure 1. CT Scan machine

Medical images taken of the human body are acquired or displayed in three main orientations:

- **Coronal** orientation: in a cross section (plane), for example, across the shoulders, dividing the body into front and back halves. An axial CT looks at the liver from below in a series of images starting at the chin and moving to the top of the head.
- **Sagittal** orientation: in a cross section (plane), for example, down the middle, dividing

the body into left and right halves A Sagittal CT looks at the liver from the side in a series of images starting at one ear and moving to the other.

- **Axial** orientation: in a cross section (plane), perpendicular to the long axis of the body, dividing the body into upper and lower halves. A coronal CT looks at the liver from behind in a series of images starting at the back of the head and moving to the face.

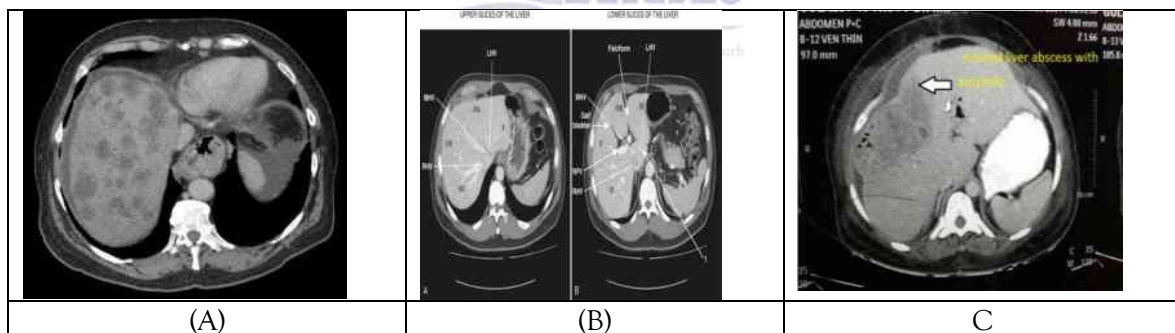


Figure 2.(A) shows axial image of liver CT, (B) shows Sagittal view of liver CT, (C) shows Coronal view of liver CT

CT units use strong electromagnetic fields and radiofrequency (RF) radiation to translate hydrogen nuclei distribution in body tissue into computer-generated images of anatomic structures. CT is an imaging technique that uses the magnetic properties of the hydrogen atom to produce images. The nucleus of hydrogen is a spinning charge proton with magnetic properties.

Two magnetic fields are used in CT.

- The first being a strong static magnetic field which causes the hydrogen atom in the bodies to align in a direction parallel to the field.
- A second magnetic field (radio-frequency RF pulse) is applied at right-angle to the first field causing the hydrogen atoms to change their alignments.

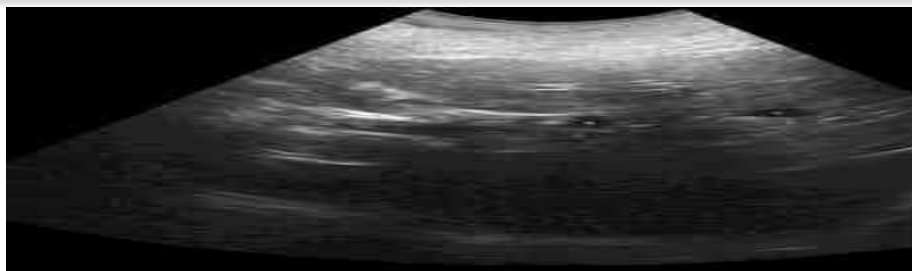


Figure 3. A Liver image scanned through CT modality

Any time a patient comes into the hospital, the doctors will have to perform some type of diagnostic test. The testing helps the medical staff to find out exactly what a patient is suffering from. Testing can even be a great way to find out about a medical condition early, before it has time to develop into a serious problem. While there are many kinds of tests they can all be placed into two different categories: Invasive and Non-invasive.

An invasive diagnostic test is any type of medical test that requires physicians to use instrumentation to physically enter the body. The instrument can be very small and relatively pain free, as is the case with taking a blood sample or more involved, as with a biopsy. Invasive diagnostics generally involve the medical professional looking inside the body to identify a potential medical issue or removing a part of the body that will be tested. Sometimes doctors use medical devices fitted with cameras or other technologically based equipment to evaluate a patient. If the test is apt to be painful, patients will either be medicated or sedated.

Medical applications increase the use of automated detection and diagnosis of diseases. The automated pathological assessment of anatomical structures is very important in clinical environments. The main objective of the research study is to investigate the methods that could represent human liver in colored version so that segmentation process be facilitated in good manners. It is also the prime objective of the study that such that information present in gray scale be converted into colored version without loss of the medical traits of the subjects. The summarized, focused and specific objectives of this research work are as under;

(a) Provide an automatic or semi-automatic colorization method to represent gray information of human liver scanned through CT imaging modality.

(b) Explore the performance of the proposed method with state-of-the-art method.

1.3.1 Research Methodology

The proposed method has converted gray scale CT lungs images into colored ones. A gray image has only luminance or intensity value I to represent a pixel ranging from 0 to 255, whereas a color image may use RGB color space with red, green and blue components. Human eye cannot identify two contiguous colors of visible spectrum, unless there is significant change in saturation. Starting from 400nm to 700nm, there are total 301 unique colors. Since each two contiguous colors are not perceivable human. Empirically, to derive the criterion (C) for colorization process, we made experiments on data set of 29 subjects that describes how many consecutive color pixels are to drop to select next pixel from color spectrum. This criterion best matches to give appropriate and considerable variations among tissues. Next derivable is the threshold (T), that determines the successfulness of the comparison using Euclidean Distance. The minimum value of T can be 1 (one), but if the value of T is adjusted at 1, the number of colors that are assigned is reduced, resultantly, in-homogeneities in color pixels are observed. Both derivations are sufficient to produce good results for soft brain tissues utilized in proposed colorization method.

2 Literature Review

Researchers established several methods to color human soft tissues acquired through medical imaging devices including liver MRI images. Each of the methods has its own pros and cons. Almost all these methods produce color images based upon estimated colors. Attique et al., [88] calculate luminance of each MRI image pixel and converts into CIELab using XYZ and then converges the color mapping process. There is an

extra overhead conversion from RGB to CIE lab and vice versa in this proposed method of colorization and is computationally not efficient. For grayscale images and videos V. G. Jacob and S. Gupta [89] proposed a semiautomatic approach to color. The algorithm requires position and color of the marker then few reference frames are manually selected to colorize using these markers and their chrominance information is then transferred to the other frames of the video. Operator involvement is the main drawback with this approach. The Luminance along-with texture has been used to find best matching source pixel. Then its chromaticity is assigned to target pixel by retaining its luminance value by Rathore, Yogesh et al., [90]. Although an automated approach is the proposed one but construction of image databases along with their parameters is also overhead. C. Sauvaget et al., [91] suggested an automatic gray image colorization approach in which user defines color from chromatic hue wheel. Bochko V et al. [92] suggested medical image colorization using support vector machine as a learning method to learn from set of images. They applied their method of colorization on dental and skin images wounded images, hence data set to learn is the requirement of the proposed medical image colorization. Holland GN and Bottomley PA [93] proposed color display technique for NMR images. MATLAB also colors the gray images and supports different types of color-maps (hot, summer etc.). Users are allowed to define their own color-map and color ranges, then linear mapping is used to assign colors to a gray image. Minimum and maximum values are calculated from source grayscale image and defined color-map. After calculation of these maximum and minimum values, the minimum gray value of the source image is replaced by calculated minimum color value while maximum gray value of the source image is replaced by calculated maximum color value. The values of gray scale image that are in between minimum and maximum are linearly replaced by the middle colors from color-map colors [94]. Colorization methods based on multi-parametric MRI images have also been reported. Different sequences of same anatomical position have been utilized during

colorization procedure, in such a way that T1w sequence is assigned red channel, T2w sequence is assigned blue channel, while FLAIR sequence is assigned green channel. After these primary channel assignments to individual sequences, these images are fused, resultantly a color image is embodied by Weiss, Kenneth L et al. [95]. Weiss KL et al. [96] has also reported multi-parametric based colorization solution for gray scale images. Two MRI images of same anatomical position scanned with different pulse sequences are used. Hue and luminance of corresponding pixels of both images is calculated to generate colored one. Similar nature of work based on multi-sequence has also been reported by Hernández, Maria del C Valdés et al. [97]. Thus, there is a need to investigate more efficient methods of colorization. Because color representation of same grayscale image enhances visual appeal. If such tools are matured, the assessment process on monochrome data will be more accurate and definitive.

In the proposed method of liver MRI colorization, MRI image is colorized in easy and efficient way. The overheads present in the reported techniques [95, 97] has been reduced. As there is no separate process to color each sequence, allied with fusion process to obtain colored image. The colorization process based on these multi phases is generally a costly solution in terms of computational complexity. Since, change in gray value of any pixel can cause artifacts. Therefore, the proposed method of colorization pertains to the original gray value of each colorization procedure. The methods provide by MATLAB to color gray scale images don't retain original luminosity [94]. Major gain to using single image colorization is that it works equally on other medical imaging modalities such as OCT, CT, X-Ray etc. where there is only one parameter available for image acquisition. In this study, a method of colorization to gray scale liver MRI images has been reported to enhance their visual perception and enabling more precise tissue discrimination. Drawing upon the human visual system's ability to discriminate colors well, the proposed methodology can become useful in enhancing the information content of monochrome MR (and potentially other modality) images. This research would be contribution for modeling

and designing reliable systems to assist radiologists, neurosurgeons, and healthcare practitioners for better analysis pertaining classification of liver tumor, localization of liver tumor, treatment planning, monitoring of therapy, pathological assessment of growth and disorders of liver soft tissues and studying the differences of healthy subjects and subjects with tumor.

A Digital image is a two-dimensional array, or a matrix, of square pixels (picture elements) arranged in columns and rows. A digital image is composed of a finite number of elements called pixels (short for picture elements), each of which has a particular location and value. Each pixel represents the colour (or gray level for black and white photos) at a single point in the image, so a pixel is like a tiny dot of a particular colour [98].

A digital image is rectangular array of pixels sometimes called a bitmap. Digital images are electronic representations of images that are stored on a computer. The most important thing to understand about digital images is that you can't see them and they don't have any physical size until they are displayed on a screen or printed on paper. Until that point, they are just a collection of numbers on the computer's hard drive that describe the individual elements of a picture and how they are arranged. These elements are called pixels (short for picture elements), and they are arranged in a grid format with each pixel containing information about its color or intensity[99].

Image pixels are represented in a 1D array in memory. We access it through pointers. While reading the rest of the code, one should keep in mind that pointers are only addresses. Even though the image is a 2D structure, for convenience and ease of processing & speed, it is a common technique to represent it as a 1D structure.

There are several ways of storing pictures on your computer, each with its own advantages and disadvantages. For example, some formats reduce the file size, but others store extra information to assist with editing the picture.

3 Methodology

As recently as few years ago, most radiologists only had available pictures of several cross sections of a liver plus their own 3D

reconstruction abilities to make a clinical diagnosis or to evaluate the result of a therapy on a patient. They use their experience and the knowledge they gain from their medical studies to diagnose the images. If we show a particular set of liver images of a patient acquired by CT to different radiologists around the world, they may diagnose the images differently. Each of them may have their own opinion about the CT images. This may lead to ambiguous results increasing the chances of errors in reports. So, there is a necessity of providing them with an automated system that diagnoses the images reducing the chances of error as in case different radiologists may give different opinions.

The necessity of providing radiologists with high contrast and noise-free images played a vital role in the development of modern CT. They provide a powerful tool for visualization and diagnosis of various human body parts including liver.

A major issue for the development of several neurological applications for CT, such as quantitative analysis, surgical operation planning, image-guided surgery or functional mapping, is the elaboration of specialized image processing techniques. These image processing techniques include segmentation techniques with automatic segmentation. Segmentation is particularly difficult due to low-contrast between tissues which even renders their manual delineation difficult, and also to high topologic variations of the structures amongst individuals [100].

The main objective is to develop a system that provides efficient image segmentation techniques for processing CT liver images.

The main requirement for a segmentation system is to have the following characteristics:

1. The system should be as automatic as possible to avoid errors due to user interaction.
2. It should be adoptable to intensity variations essentially due to magnetic field inhomogeneities.
3. It should be able to cope with shape and topology variations of the liver structure.

3.1 Image Acquisition

The images have been obtained on a CT scanner. The experimental work has been performed under institutional laws of Bahawal

Victoria Hospital (BVH) Bahawalpur, Pakistan. These laws were validated by institutional review and ethical committees. The participants/patients were informed and signed the consent of data acquisition before measurements in the department of radiology and diagnostic images. Bahawal Victoria Hospital Bahawalpur, Pakistan.

CT images were obtained from total 49 subjects (35 males and 14 females, 35 normal and 14 abnormal) of average 39 years old patients having stroke, hemorrhage, tumors and multiple sclerosis. Amongst them 29 subjects (22 males and 07 females, 21 normal and 08 abnormal) were used to derive criteria for colorization as shown in Table 1. Rest of the 20 subjects (13 males and 07 females, 14 normal and 06 abnormal) were used to derive threshold. All the subjects were used to obtained results for the verification of proposed method of colorization. The colorization model is represented with the block diagram shown in Figure 1. Author [31]

was consulted to obtain expert opinion and validation of the outcomes.

3.2 Preprocessing

Histogram-based segmentation depends on the histogram of the image. Therefore, you must prepare the image and its histogram before analyzing it. The first step is histogram equalization. Histogram equalization attempts to alter an image, so its histogram is flat and spreads out over the entire range of gray levels. The result is an image with better contrast. Calculate the histogram, equalize the histogram and then filter the histogram to achieve the goal. These steps are part of our preprocessing.

Histo Gram

The histogram of an image shows us the distribution of grey levels in the image. It is massively useful in image processing, especially in segmentation.

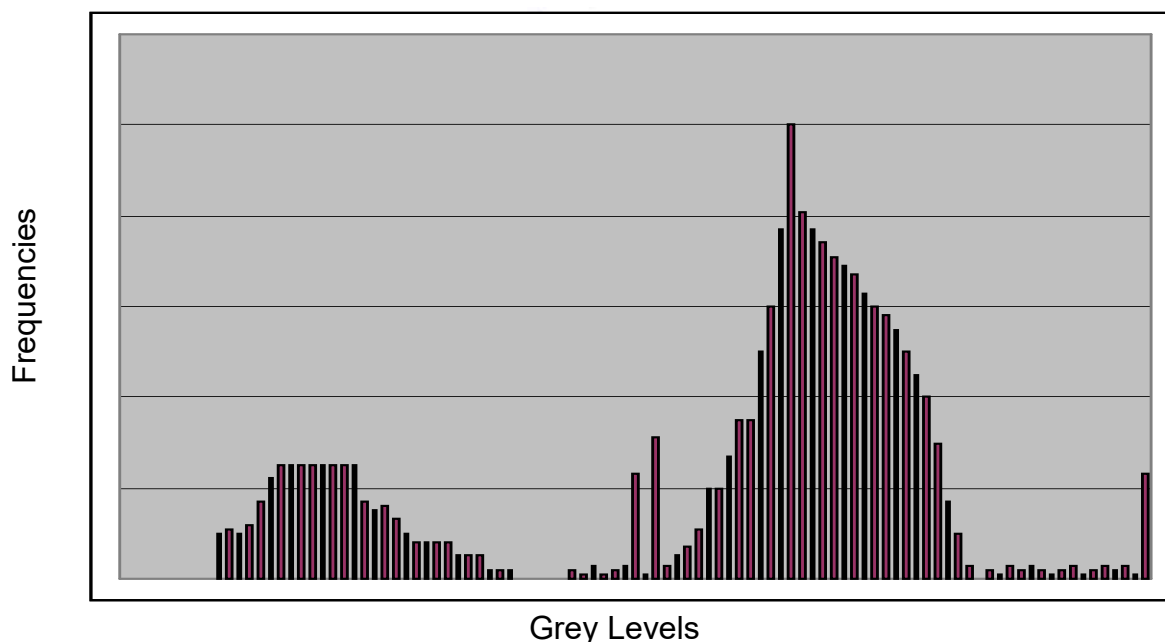


Figure 4. Histogram Sample

Image histograms are an important concept in Image Processing. The histogram of an image refers to the histogram of the intensity values of the pixels. It displays the no of pixels in an image for a particular intensity level.

The x-axis in the image histogram comprises of the intensity values (0-255 in case of 8-bit depth image) and the height of the bar displays the number of pixels with that intensity value.

The histogram with the image is given below:

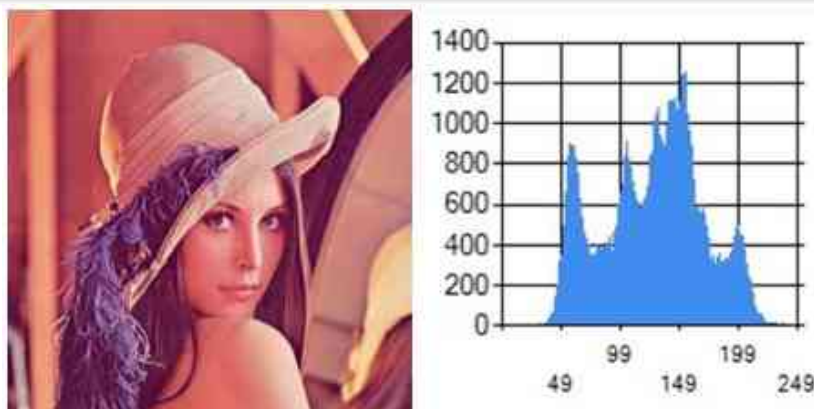


Figure 5. Image of Lena and its Histogram

To convert gray scale brain MRI images into colored ones a colorization method has been proposed. A gray image has only luminance or intensity value I to represent a pixel ranging from 0 to 255, whereas a color image may use RGB color space with red, green and blue components. Human eye cannot identify two contiguous colors of visible spectrum, unless there is significant change in saturation. Starting from 400nm to 700nm, there are total 301 unique colors. Since, each two contiguous colors are not perceivable human. Empirically, to derive the criterion (C) for colorization process, we made experiments on data set of 29 subjects that describes how many consecutive color pixels

are to drop to select next pixel from color spectrum. This criterion best matches to give appropriate and considerable variations among tissues. Next derivable is the threshold (T), that determines the successfulness of the comparison using Euclidean Distance. The minimum value of T can be 1 (one), but if the value of T is adjusted at 1, the number of colors that are assigned is reduced, resultantly, inhomogeneities in color pixels are observed. Both derivations are sufficient to produce good results for soft brain tissues utilized in proposed colorization method. Table 1 shows the details of the subjects used to derive both C and T .

Table 1. Subjects examined for both C and T .

Criteria	Total Subjects	Imaging	Normal/Abnormal	Male/Female
Color Gap (C)	29	CT Liver	21/08	22/07
Threshold (T)	20	CT Liver	14/06	13/07

Here are the steps of the proposed algorithm used for brain soft tissues colorization process utilizing the visible spectrum ranging from 400nm to 700nm frequencies. The top-down approach this proposed paradigm is depicted in Figure 3.3.

3.1Algorithm Steps

1. Input gray scale brain MRI image (I_g).
2. Input linear vector (I_c) containing visible color spectrum ranging from 400nm to 700nm frequencies.
3. Input C and T calculated after analysis of subjects as shown in Table 1.

4. Repeat: read individual pixels (P_i) of I_g
5. Calculate Intensity (I) of P_i
 - a. Repeat: read pixel (P_c) from I_c
 - b. Calculate intensity (i) of P_c
 - c. If ($ABS(I-i) \leq T$) Then
 - i. Replace P_i with P_c
 - ii. Goto step 4
 - d. Else
 - i. Skip no. of pixels from I_c , equal to C
 - ii. Goto step 5 (a)
 - e. End If
 - f. End Repeat
 6. End Repeat

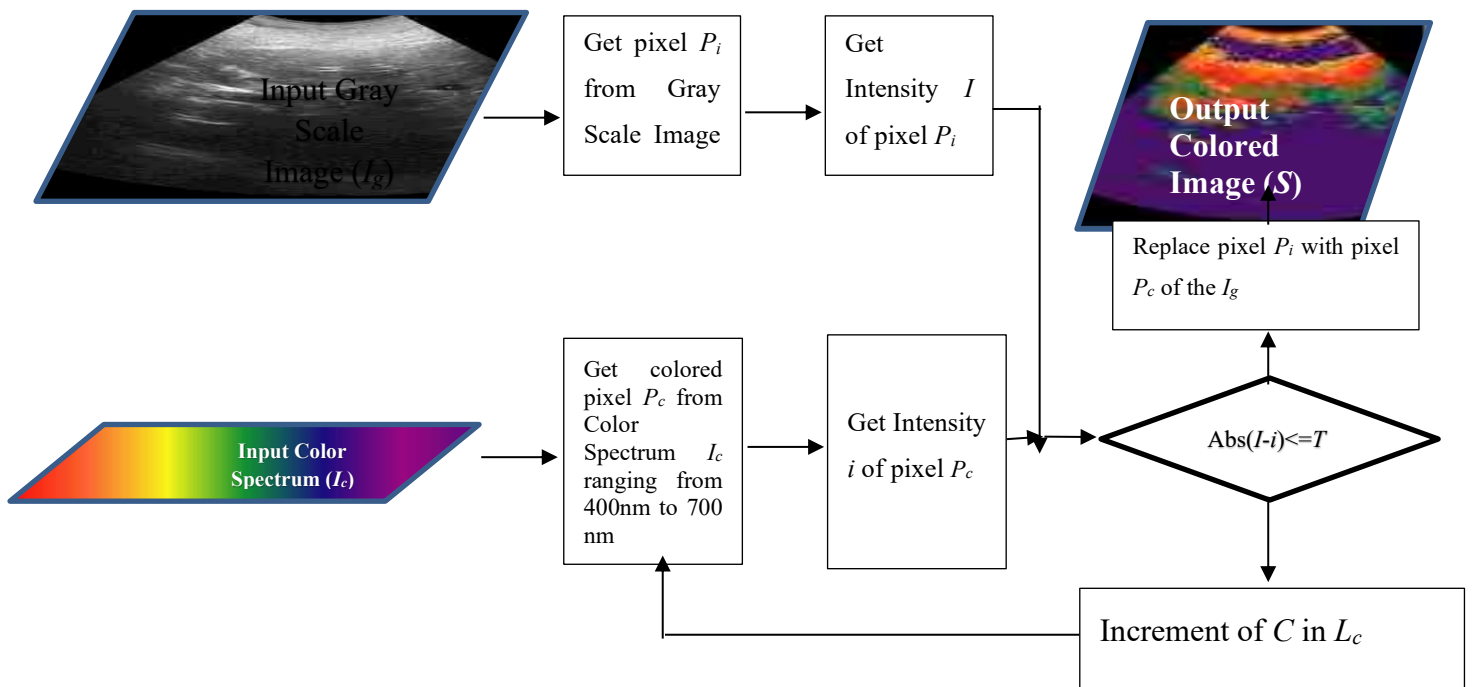


Figure 6. Showing the top-down approach for colorization of liver soft tissues using visible color spectrum ranging from 400nm to 700nm

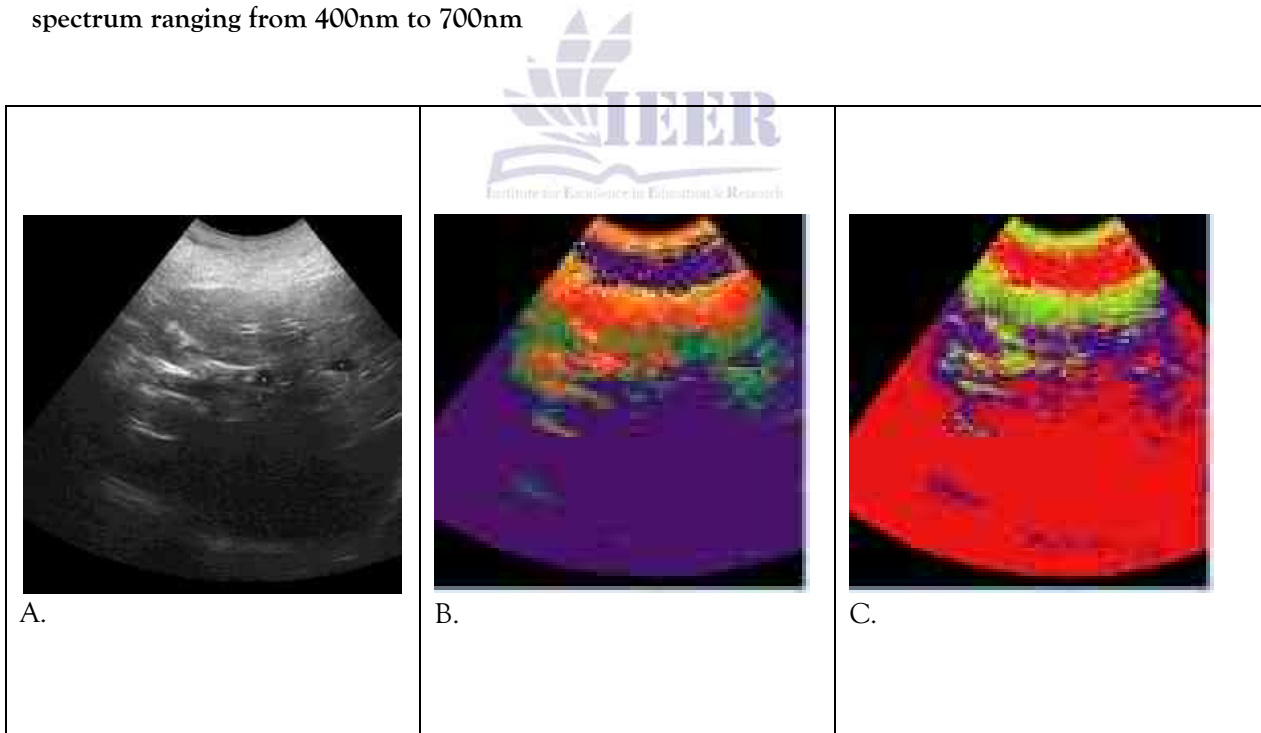


Figure 7. (A) Shows T2w Liver Image with dimension 256X256, (B) Shows colored image using 400 to 700 nm visible spectrum (C) Shows colored images using visible spectrum from 700nm to 400 nm

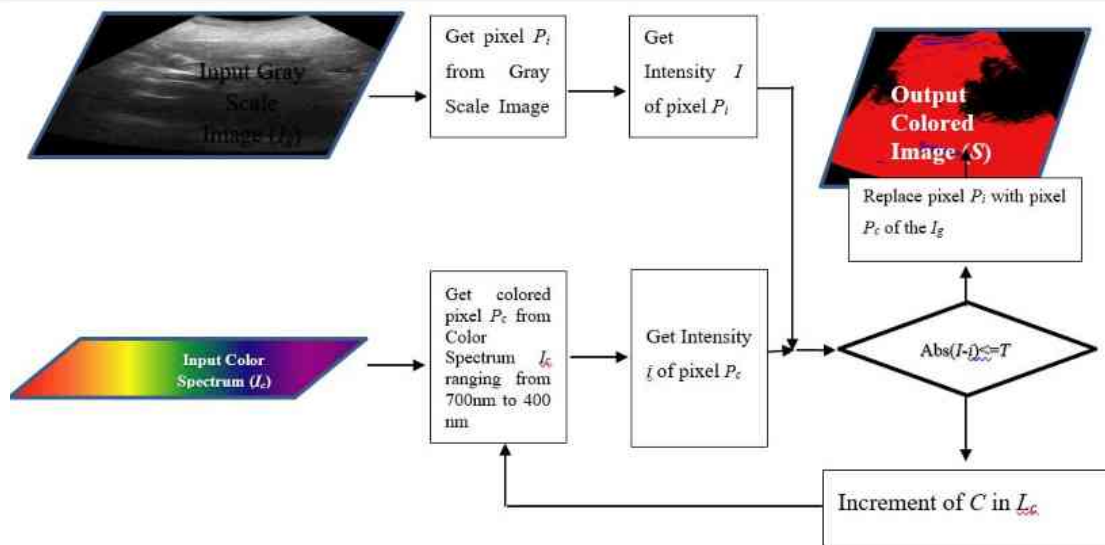


Figure 8 Showing the top down approach for colorization of liver soft tissues using visible color spectrum ranging from 700nm to 400nm

3.3

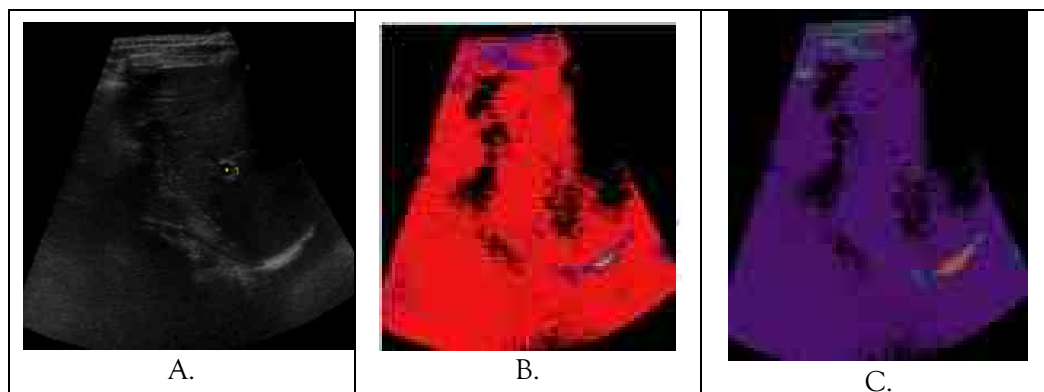


Figure 9. (A) Shows T2w Liver Image with dimension 256X256, (B) Shows colored image using 400 to 700 nm visible spectrum (C) Shows colored images using visible spectrum from 700nm to 400 nm

4 Results & Discussion

The basic purpose of this conducted research is to provide ease to radiologists, radio oncologists, medical practitioners, physicians, and general surgeons working in different medial units in identifying and interpreting the CT images with more definite and accurate manners. I have colored the liver tissues in both fully automated and semi-automated fashion. In both ways of implementing the proposed system, the results

obtained remained acceptable by the domain experts. According to their visual and subjective analysis, the overall system is appreciative. First, the results obtained through fully automated way are presented as following (first column shows the gray scale CT image and its segments, second column shows colored image using 400 to 700 nm visible spectrum, and third column shows colored images using visible spectrum in reverse order i.e. 700 to 400 nm).

4.1 Results obtained through fully automated developed tool

IMAGE 1:

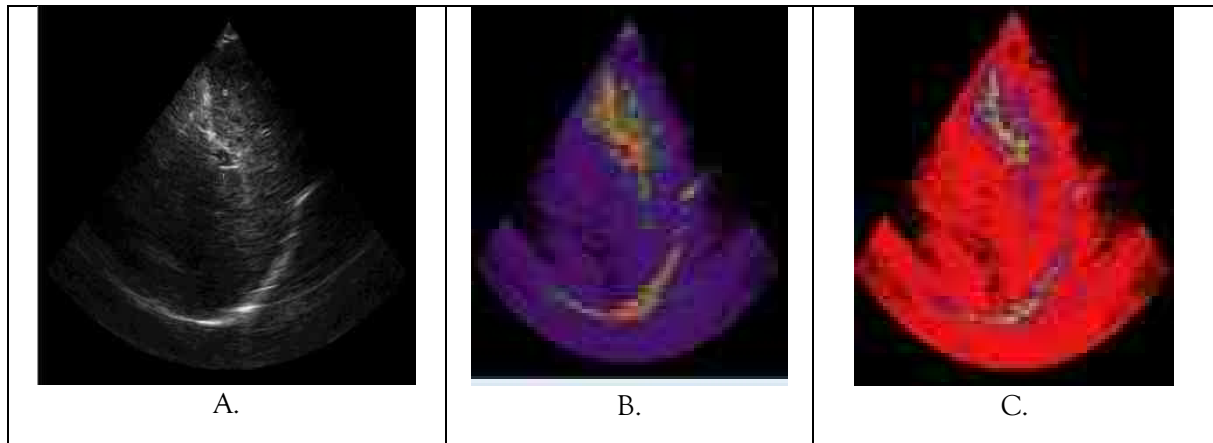


Figure 10. Showing result obtained from T2W Liver CT Image with dimension 256X256. First column shows the gray scale CT image and its segments, second column shows colored image using 400 to 700 nm visible spectrum, and third column shows colored images using visible spectrum in reverse order i.e. 700 to 400 nm

IMAGE 2:

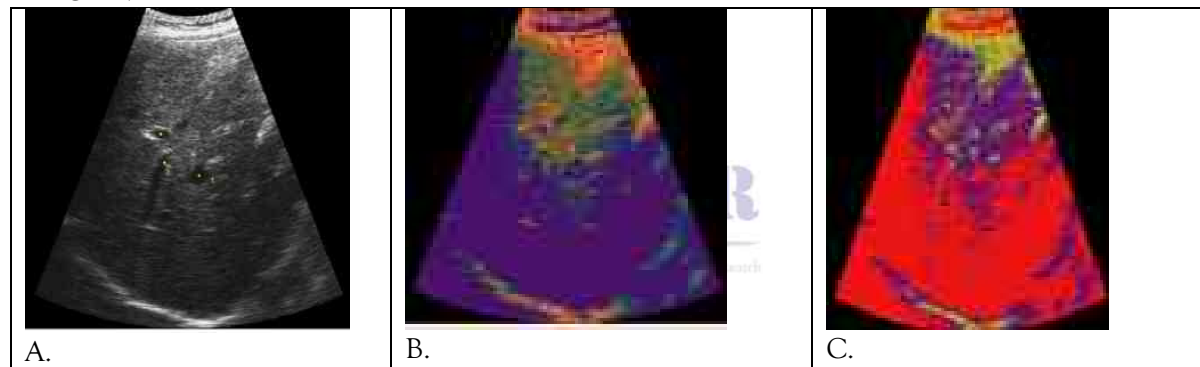


Figure 11. Showing result obtained from T2W Liver CT Image with dimension 256X256. First column shows the gray scale CT image and its segments, second column shows colored image using 400 to 700 nm visible spectrum, and third column shows colored images using visible spectrum in reverse order i.e. from 700 to 400 nm.

Figure 11. (A) showing liver CT image with dimensions 256X256 (B) 400 to 700 nm colored version of image (A), (C) 700 to 400 nm colored version of image (A).

The above figure shows the normal liver image with a little liver atrophy. The detail of soft

tissues is more clearly visible because of colorization. Figure shows the detail of the skin, scalp and meninges can be easily made out if there is any abnormality in these structures, that will be more easily picked up by human eye because of color rendering.

IMAGE 3:

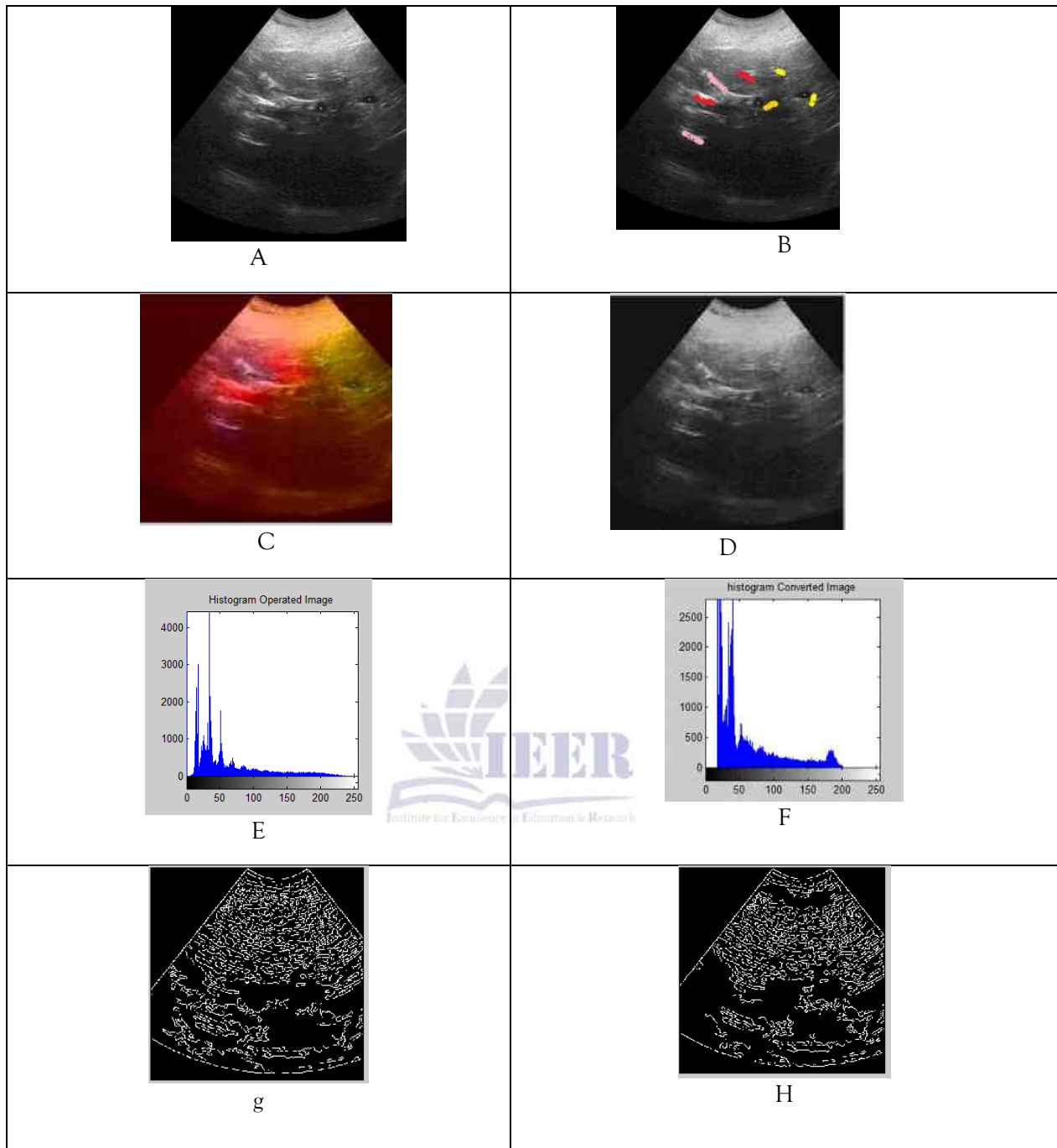


Figure 12. shows output of the proposed method. (a) Original gray scale image of Liver (b)Annotated image by specialist/radiologist (c)Resultant image by proposed method (d)Gray scale conversion of (c), (e)Histogram of original image(a), (f)Histogram of Gray scale image(d), (g)Edges detected through Canny model of (a), (h)Edges detected through canny model of(d).

IMAGE 4:

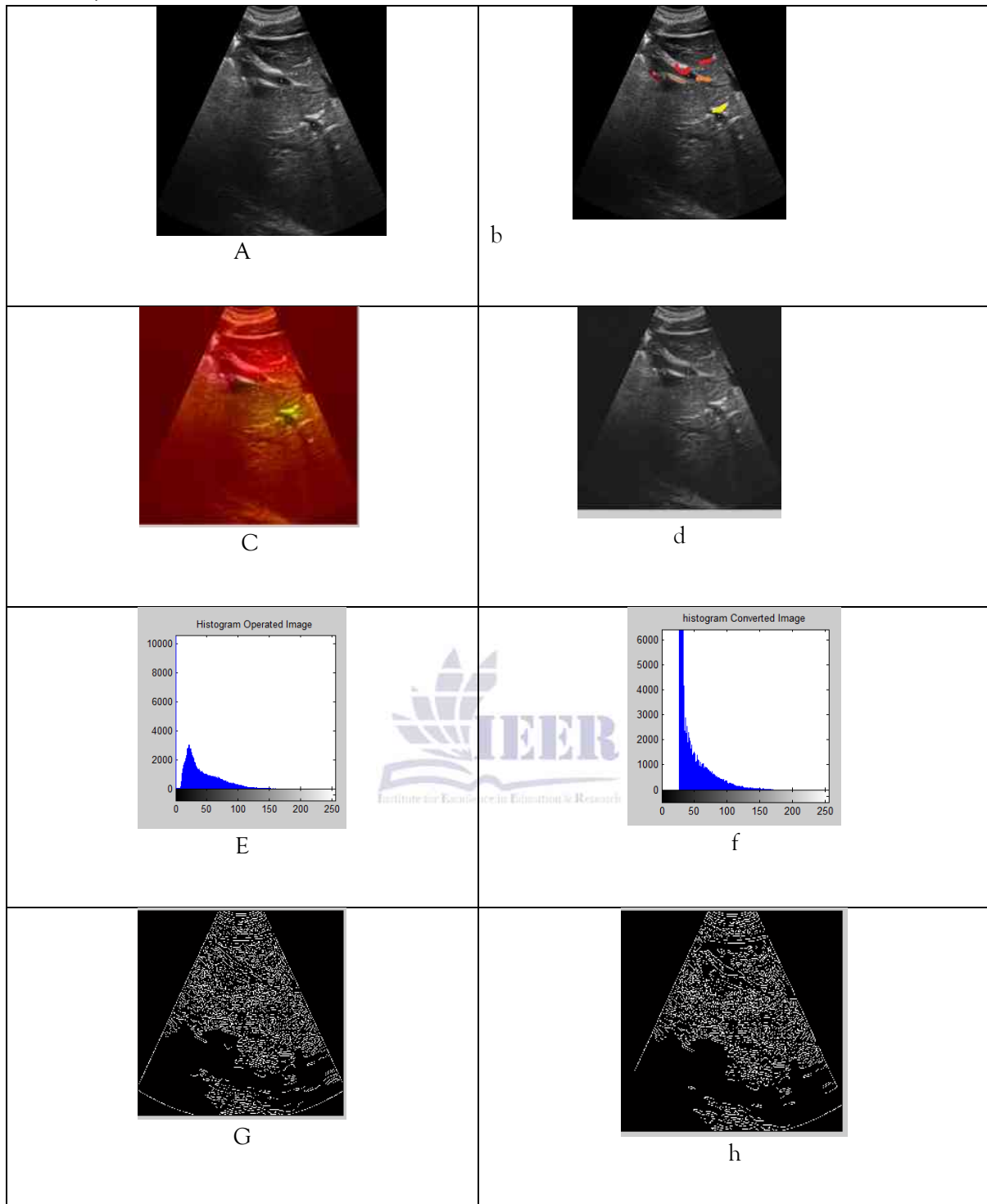


Figure 13 shows output of the proposed method. (a) Original gray scale image of Liver (b)Annotated image by specialist/radiologist (c)Resultant image by proposed method (d)Gray scale conversion of (c), (e)Histogram of original image(a), (f)Histogram of Gray scale image(d), (g)Edges detected through Canny model of (a), (h)Edges detected through canny model of(d).

IMAGE 5:

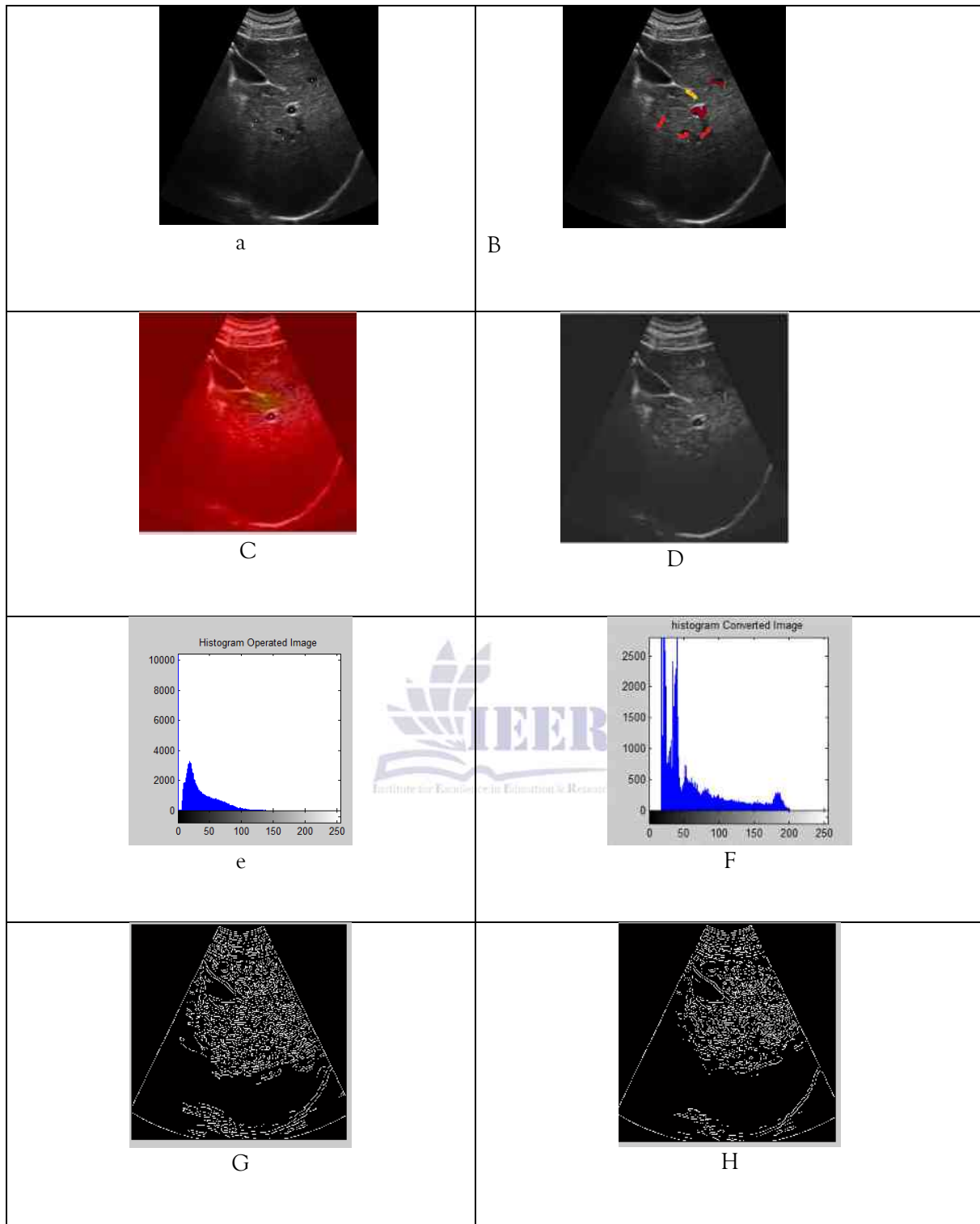


Figure 14. shows output of the proposed method. (a) Original gray scale image of Liver (b)Annotated image by specialist/radiologist (c)Resultant image by proposed method (d)Gray scale conversion of (c), (e)Histogram of original image(a), (f)Histogram of Gray scale image(d), (g)Edges detected through Canny model of (a), (h)Edges detected through canny model of(d).

To authenticate the proposed method of colorization running in semi-automated way, I

used to color the other anatomical structures scanned through different imaging modalities.

For this, I considered, Chest image scanned through X-Ray, Hand image scanned through X-Ray, and dental image scanned through MRI medical imaging modality.

5.1 Conclusion

Image segmentation is obviously more essential feature in most image processing methods allied with CT imaging data, which reflects anatomical structure of segment (tissue). The usefulness of these methods in clinical environment significantly depends on the ease of computation and the reduction of operator involvement. The method used in this research work is based on the proposed algorithm, which performs spectroscopy to segment out possible objects from T2 weighted liver CT image. The applicability of this algorithm is practically verified. It is established that the proposed method can be applied to other medical imaging modalities or other image processing domains and it is quite efficient. Segmentation is achieved through histogram valley to valley calculation (absorbing small peaks into large peaks). GM, WM, CSF and abnormality exist with their original pixel's intensity levels are extracted and there is no loss of useful information. However, the proposed segmentation method needs improvement to deal with all other imaging modalities for the segmentation of object under analysis. The proposed segmentation method does not deal with intensity in-homogeneity. To deal with intensity in-homogeneity is another research article discussed in various literatures. The colorization method is used to colorize the gray scale CT images to enhance the visual perception and increase discrimination. The proposed methods generate appreciative results on applying to the T2 liver CT images. The results generated with the colorization method are excellently refined and clearly unveil the hidden information that is difficult to observe with naked eye from the gray scale image. In future the liver CT image segmentation method will be improved in accuracy, precision and computational speed as well as a fully automatic way. Furthermore, the different segments will be mapped into their color plotted domain after segmentation from liver CT image. The proposed method will be made so generic by using some statistical features with applications

of classification and volume calculation of liver components. Once the window size is adjusted automatically by using some statistical features then the fully automatic segmentation method will be the proposed method.

REFERENCES

- D. Shen, G. Wu, D. Zhang, K. Suzuki, F. Wang, and P. Yan, "Machine learning in medical imaging," *Computerized medical imaging and graphics: the official journal of the Computerized Medical Imaging Society*, vol. 41, pp. 1-2, 2015.
- J. Liu, M. Li, J. Wang, F. Wu, T. Liu, and Y. Pan, "A survey of MRI-based brain tumor segmentation methods," *Tsinghua Science and Technology*, vol. 19, no. 6, pp. 578-595, 2014.
- A. Işık *et al.*, "How could such a wide piece of tree root pass through the narrow pyloric orifice? An extremely rare case," *The American journal of case reports*, vol. 15, p. 284, 2014.
- A. Isik, K. Peker, M. Soyuturk, D. Firat, U. Yoruker, and I. Yilmaz, "Diagnostic evaluation and treatment of patients with rectus abdominis hematoma," *Cirugía Española (English Edition)*, vol. 93, no. 9, pp. 580-588, 2015.
- E. A. Khera *et al.*, "Characterization of Nickel Oxide Thin Films for Smart Window Energy Conversion Applications: Comprehensive Experimental and Computational Study," *Available at SSRN 4235112*.
- M. Attique *et al.*, "Colorization and automated segmentation of human T2 MR brain images for characterization of soft tissues," *PLoS one*, vol. 7, no. 3, p. e33616, 2012.
- H. Ullah, G. Gilanie, M. Attique, M. Hamza, and M. Ikram, "M-mode swept source optical coherence tomography for quantification of salt concentration in blood: an in vitro study," *Laser Physics*, vol. 22, pp. 1002-1010, 2012.
- G. Gilanie, "Spectroscopy of T2 weighted brain MR image for object extraction using prior anatomical knowledge based spectroscopic histogram analysis," 2013.

- G. Gilanie, M. Attique, S. Naweed, E. Ahmed, and M. Ikram, "Object extraction from T2 weighted brain MR image using histogram based gradient calculation," *Pattern Recognition Letters*, vol. 34, no. 12, pp. 1356-1363, 2013.
- H. Ullah, G. Gilanie, F. Hussain, and E. Ahmad, "Autocorrelation optical coherence tomography for glucose quantification in blood," *Laser Physics Letters*, vol. 12, no. 12, p. 125602, 2015.
- K. Asghar, G. Gilanie, M. Saddique, and Z. Habib, "Automatic Enhancement Of Digital Images Using Cubic BÃ©zier Curve And Fourier Transformation," *Malaysian Journal of Computer Science*, vol. 30, no. 4, pp. 300-310, 2017.
- H. U. Janjua, F. Andleeb, S. Aftab, F. Hussain, and G. Gilanie, "Classification of liver cirrhosis with statistical analysis of texture parameters," *International Journal of Optical Sciences*, vol. 3, no. 2, pp. 18-25, 2017.
- U. I. Bajwa, A. A. Shah, M. W. Anwar, G. Gilanie, and A. Ejaz Bajwa, "Computer-aided detection (CADE) system for detection of malignant lung nodules in CT slices-a key for early lung cancer detection," *Current Medical Imaging*, vol. 14, no. 3, pp. 422-429, 2018.
- G. Gilanie, U. I. Bajwa, M. M. Waraich, Z. Habib, H. Ullah, and M. Nasir, "Classification of normal and abnormal brain MRI slices using Gabor texture and support vector machines," *Signal, Image and Video Processing*, vol. 12, pp. 479-487, 2018.
- G. Gilanie, H. Ullah, M. Mahmood, U. I. Bajwa, and Z. Habib, "Colored Representation of Brain Gray Scale MRI Images to potentially underscore the variability and sensitivity of images," *Current Medical Imaging Reviews*, vol. 14, no. 4, pp. 555-560, 2018.
- H. U. Janjua, A. Jahangir, and G. Gilanie, "Classification of chronic kidney diseases with statistical analysis of textural parameters: a data mining technique," *International Journal of Optical Sciences*, vol. 4, no. 1, pp. 1-7, 2018.
- H. Ullah, A. Batool, and G. Gilanie, "Classification of Brain Tumor with Statistical Analysis of Texture Parameter Using a Data Mining Technique," *International Journal of Industrial Biotechnology and Biomaterials*, vol. 4, no. 2, pp. 22-36, 2018.
- G. Gilanie, "Automated Detection and Classification of Brain Tumor from MRI Images using Machine Learning Methods," Department of Computer Science, COMSATS University Islamabad, Lahore campus, 2019.
- G. Gilanie, U. I. Bajwa, M. M. Waraich, and Z. Habib, "Automated and reliable brain radiology with texture analysis of magnetic resonance imaging and cross datasets validation," *International Journal of Imaging Systems and Technology*, vol. 29, no. 4, pp. 531-538, 2019.
- G. Gilanie, U. I. Bajwa, M. M. Waraich, and Z. Habib, "Computer aided diagnosis of brain abnormalities using texture analysis of MRI images," *International Journal of Imaging Systems and Technology*, vol. 29, no. 3, pp. 260-271, 2019.
- K. Van Leemput, F. Maes, D. Vandermeulen, and P. Suetens, "Automated model-based tissue classification of MR images of the brain," *Medical Imaging, IEEE Transactions on*, vol. 18, no. 10, pp. 897-908, 1999.
- S. Ruan, C. Jaggi, J. Xue, J. Fadili, and D. Bloyet, "Brain tissue classification of magnetic resonance images using partial volume modeling," *Medical Imaging, IEEE Transactions on*, vol. 19, no. 12, pp. 1179-1187, 2000.
- Y. Zhang, M. Brady, and S. Smith, "Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm," *Medical Imaging, IEEE Transactions on*, vol. 20, no. 1, pp. 45-57, 2001.

- K. H. Oh, S. H. Kim, and M. Lee, "Tumor detection on brain MR images using regional features: Method and preliminary results," in *Frontiers of Computer Vision (FCV), 2015 21st Korea-Japan Joint Workshop on*, 2015, pp. 1-4: IEEE.
- J. J. Corso, E. Sharon, S. Dube, S. El-Saden, U. Sinha, and A. Yuille, "Efficient multilevel brain tumor segmentation with integrated bayesian model classification," *Medical Imaging, IEEE Transactions on*, vol. 27, no. 5, pp. 629-640, 2008.
- E. I. Zacharaki *et al.*, "Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme," *Magnetic Resonance in Medicine*, vol. 62, no. 6, pp. 1609-1618, 2009.
- A. Mayer and H. Greenspan, "An adaptive mean-shift framework for MRI brain segmentation," *Medical Imaging, IEEE Transactions on*, vol. 28, no. 8, pp. 1238-1250, 2009.
- M. Amjad, H. Ullah, F. Andleeb, Z. Batool, A. Nazir, and G. Gilanie, "Fourier-Transform Infrared Spectroscopy (FTIR) for Investigation of Human Carcinoma and Leukaemia," *Lasers in Engineering (Old City Publishing)*, vol. 51, 2021.
- G. Gilanie, U. I. Bajwa, M. M. Waraich, and M. W. Anwar, "Risk-free WHO grading of astrocytoma using convolutional neural networks from MRI images," *Multimedia Tools and Applications*, vol. 80, no. 3, pp. 4295-4306, 2021.
- G. Gilanie *et al.*, "Coronavirus (COVID-19) detection from chest radiology images using convolutional neural networks," *Biomedical Signal Processing and Control*, vol. 66, p. 102490, 2021.
- G. Gilanie *et al.*, "RiceAgeNet: Age Estimation of Pakistani Grown Rice Seeds using Convolutional Neural Networks," *International Journal of Computational Intelligence in Control*, vol. 13, no. 2, pp. 831-843, 2021.
- G. Gilanie, N. Nasir, U. I. Bajwa, and H. Ullah, "RiceNet: convolutional neural networks-based model to classify Pakistani grown rice seed types," *Multimedia Systems*, pp. 1-9, 2021.
- G. Gilanie *et al.*, "Digital Image Processing for Ultrasound Images: A Comprehensive," *Digital Image Processing*, vol. 15, no. 3, 2021.
- S. Malik *et al.*, "Enhancing Contrast in Optical Imaging of Cancer tissues and Study the Spectral Properties of Methylene Blue," *Acta Microscópica*, vol. 30, no. 2, pp. 49-57, 2021.
- M. Rafiq, U. I. Bajwa, G. Gilanie, and W. Anwar, "Reconstruction of scene using corneal reflection," *Multimedia Tools and Applications*, pp. 1-17, 2021.
- A. A. Ghaffar *et al.*, "Refined Sentiment Analysis by Ensembling Technique of Stacking Classifier," in *International Conference on Soft Computing and Data Mining, 2022*, pp. 380-389: Springer.
- G. Gilanie *et al.*, "An Automated and Real-time Approach of Depression Detection from Facial Micro-expressions," *Computers, Materials & Continua*, vol. 73, no. 2, 2022.
- G. Gilanie, N. Rehman, U. I. Bajwa, S. Sharif, H. Ullah, and M. F. Mushtaq, "FERNet: A Convolutional Neural Networks Based Robust Model to Recognize Human Facial Expressions," in *International Conference on Soft Computing and Data Mining, 2022*, pp. 353-360: Springer.
- M. J. Iqbal, U. I. Bajwa, G. Gilanie, M. A. Iftikhar, and M. W. Anwar, "Automatic brain tumor segmentation from magnetic resonance images using superpixel-based approach," *Multimedia Tools And Applications*, vol. 81, no. 27, pp. 38409-38427, 2022.
- S. F. Rubab *et al.*, "The Comparative Performance of Machine Learning Models for COVID-19 Sentiment Analysis," in *International Conference on Soft Computing and Data Mining, 2022*, pp. 371-379: Springer.

- H. Ullah, M. Faran, Z. Batool, A. Nazir, G. Gilanie, and N. Amin, "Diagnosis of Ocular Diseases Using Optical Coherence Tomography (OCT) at $\lambda=840$ nm," *Lasers in Engineering (Old City Publishing)*, vol. 53, 2022.
- E. Wazir, G. Gilanie, N. Rehman, H. Ullah, and M. F. Mushtaq, "Early Stage Detection of Cardiac Related Diseases by Using Artificial Neural Network," in *International Conference on Soft Computing and Data Mining, 2022*, pp. 361-370: Springer.
- M. Yaseen *et al.*, "In-vitro Evaluation of Anticancer Activity of Rhodamine-640 perchlorate on Rhabdomyosarcoma cell line," 2022.
- F. Afzal *et al.*, "Detection of Uric Acid in UV-VIS wavelength Regime," *JOURNAL OF NANOSCOPE (JN)*, vol. 4, no. 1, pp. 75-81, 2023.
- M. Ahmed, G. Gilanie, M. Ahsan, H. Ullah, and F. A. Sheikh, "Review of Artificial Intelligence-based COVID-19 Detection and A CNN-based Model to Detect Covid-19 from X-Rays and CT images," *VFAST Transactions on Software Engineering*, vol. 11, no. 2, pp. 100-112, 2023.
- S. Asghar *et al.*, "Water classification using convolutional neural network," *IEEE Access*, vol. 11, pp. 78601-78612, 2023.
- S. N. Batool and G. Gilanie, "CVIP-Net: A Convolutional Neural Network-Based Model for Forensic Radiology Image Classification," *Computers, Materials & Continua*, vol. 74, no. 1, 2023.
- M. Ghani and G. Gilanie, "The IOMT-Based Risk-Free Approach to Lung Disorders Detection from Exhaled Breath Examination," *INTELLIGENT AUTOMATION AND SOFT COMPUTING*, vol. 36, no. 3, pp. 2835-2847, 2023.
- G. Gilanie, U. I. Bajwa, M. M. Waraich, M. W. Anwar, and H. Ullah, "An automated and risk free WHO grading of glioma from MRI images using CNN," *Multimedia tools and applications*, vol. 82, no. 2, pp. 2857-2869, 2023.
- H. A. Hafeez *et al.*, "A CNN-model to classify low-grade and high-grade glioma from mri images," *IEEE Access*, vol. 11, pp. 46283-46296, 2023.
- E. A. Khera *et al.*, "Characterizing nickel oxide thin films for smart window energy conversion applications: Combined experimental and theoretical analyses," *ChemistrySelect*, vol. 8, no. 37, p. e202302320, 2023.
- A. Nazir, H. Ullah, G. Gilanie, S. Ahmad, Z. Batool, and A. Gadhi, "Exploring Breast Cancer Texture Analysis through Multilayer Neural Networks," *Scientific Inquiry and Review*, vol. 7, no. 3, pp. 32-47, 2023.
- H. Shafiq, G. Gilanie, M. Sajid, and M. Ahsan, "Dental radiology: a convolutional neural network-based approach to detect dental disorders from dental images in a real-time environment," *Multimedia Systems*, vol. 29, no. 6, pp. 3179-3191, 2023.
- H. Ullah *et al.*, "Proteins and Triglycerides Measurement in Blood Under Ultraviolet (UV)/Visible (Vis) Spectroscopy at $\lambda=190$ to 1100 nm with an Additional He-Ne Laser Source," *LASERS IN ENGINEERING*, vol. 55, no. 3-6, pp. 157-167, 2023.
- H. Ullah *et al.*, "Assessing Graphene Oxide (GO) and CuO Nanocomposites for Effective Antibacterial Properties Using Laser Interferometry," *Lasers in Engineering (Old City Publishing)*, vol. 55, 2023.
- H. Ullah, M. Zafar, Z. Batool, A. Nazir, G. Gilanie, and J. Rehman, "Early Detection of Liver, Ovary, Breast and Stomach Tumours in the Visible ($\lambda=630$ nm) and Infrared (IR)($\lambda=10.5$ to $5.5 \mu\text{m}$) Wavelength Regimes," *Lasers in Engineering (Old City Publishing)*, vol. 54, 2023.
- G. Gilanie *et al.*, "A Robust Method of Bipolar Mental Illness Detection from Facial Micro Expressions Using Machine Learning Methods," *Intelligent Automation & Soft Computing*, vol. 39, no. 1, 2024.

- S. Naveed *et al.*, "Drug efficacy recommendation system of glioblastoma (GBM) using deep learning," *IEEE Access*, 2024.
- M. S. Rashid, G. Gilanie, S. Naveed, S. Cheema, and M. Sajid, "Automated detection and classification of psoriasis types using deep neural networks from dermatology images," *Signal, Image and Video Processing*, vol. 18, no. 1, pp. 163-172, 2024.
- A. Saher, G. Gilanie, S. Cheema, A. Latif, S. N. Batool, and H. Ullah, "A Deep Learning-Based Automated Approach of Schizophrenia Detection from Facial Micro-Expressions," *Intelligent Automation & Soft Computing*, vol. 39, no. 6, 2024.
- H. ULLAH *et al.*, "Potential application of CeO₂/Au nanoparticles as contrast agents in optical coherence tomography," *Journal of Optoelectronics and Advanced Materials*, vol. 26, no. July-August 2024, pp. 307-315, 2024.
- H. ULLAH *et al.*, "Measurements of Hyperproteinaemia in Human Blood Using Laser Interferometry: In Vitro Study," *Lasers in Engineering (Old City Publishing)*, vol. 57, 2024.
- M. Adnan *et al.*, "ETHNICITY CLASSIFICATION FROM FACIAL IMAGES USING DEEP LEARNING METHODS," *Spectrum of Engineering Sciences*, vol. 3, no. 9, pp. 1082-1156, 2025.
- A. Ahmed *et al.*, "ADAPTING IPV6 AND 6LOWPAN OVER WIFI-BASED AODV MANETS FOR IOT APPLICATIONS," *Spectrum of Engineering Sciences*, vol. 3, no. 7, pp. 1038-1052, 2025.
- M. Akhtar *et al.*, "Harnessing optics and statistics for early detection and prognosis in breast and ovarian cancer," *Lasers in Medical Science*, vol. 40, no. 1, p. 279, 2025.
- M. Amjad *et al.*, "Staging of Different Tumor by Utilizing Laser Guidance (@ 405 nm) in CT Scan Images Along with Statistical Analysis," *LASERS IN ENGINEERING*, vol. 59, no. 4-6, pp. 309-325, 2025.
- M. Amjad *et al.*, "Histopathology of Malignant Tissues Using High-Resolution Microscopy@ 630nm," *LASERS IN ENGINEERING*, vol. 59, no. 4-6, pp. 295-308, 2025.
- M. Anwaar, G. Gilanie, A. Namoun, and W. Sharif, "Optimizing Document Classification Using Modified Relative Discrimination Criterion and RSS-ELM Techniques," *International Journal of Advanced Computer Science & Applications*, vol. 16, no. 4, 2025.
- S. N. Batool *et al.*, "Forensic Radiology: A robust approach to biological profile estimation from bone image analysis using deep learning," *Biomedical Signal Processing and Control*, vol. 105, p. 107661, 2025.
- G. Gilanie *et al.*, "A ROBUST CONVOLUTIONAL NEURAL NETWORK-BASED APPROACH FOR HUMAN EMOTION CLASSIFICATION: CROSS-DATASET VALIDATION AND GENERALIZATION," *Spectrum of Engineering Sciences*, vol. 3, no. 4, pp. 782-798, 2025.
- G. Gilanie *et al.*, "A ROBUST ARTIFICIAL NEURAL NETWORK APPROACH FOR EARLY DETECTION OF CARDIAC DISEASES," *Spectrum of Engineering Sciences*, vol. 3, no. 4, pp. 499-511, 2025.
- G. Gilanie *et al.*, "DEEP LEARNING-BASED APPROACH FOR ESTIMATING THE AGE OF PAKISTANI-GROWN RICE SEEDS," *Spectrum of Engineering Sciences*, vol. 3, no. 1, pp. 557-572, 2025.
- G. Gilanie *et al.*, "STEGANOGRAPHIC SECRET COMMUNICATION USING RGB PIXEL ENCODING AND CRYPTOGRAPHIC SECURITY," *Spectrum of Engineering Sciences*, vol. 3, no. 3, pp. 323-336, 2025.
- G. Gilanie *et al.*, "READABLE TEXT RETRIEVAL FROM NOISE-INFLUENCED DOCUMENTS USING IMAGE RESTORATION METHODS," *Spectrum of Engineering Sciences*, vol. 3, no. 3, pp. 337-360, 2025.

- G. Gilanie *et al.*, "PARAMETER OPTIMIZATION OF AUTOENCODER FOR IMAGE CLASSIFICATION USING GENETIC ALGORITHM," *Spectrum of Engineering Sciences*, vol. 3, no. 4, pp. 201-213, 2025.
- A. Kashif *et al.*, "FORENSIC RADIOLOGY: AN INTELLIGENT METHOD OF AGE AND GENDER ESTIMATION FROM X-RAY SCANNED BONES IMAGES USING CONVOLUTIONAL NEURAL NETWORKS," *Spectrum of Engineering Sciences*, vol. 3, no. 7, pp. 440-487, 2025.
- A. Latif *et al.*, "A VISION-FREE OBSTACLE DETECTION AND ALERT SYSTEM USING SMART KNEE GLOVES," *Spectrum of Engineering Sciences*, vol. 3, no. 6, pp. 816-829, 2025.
- M. Sajid *et al.*, "IoMT-Enabled Noninvasive Lungs Disease Detection and Classification Using Deep Learning-Based Analysis of Lungs Sounds," *International Journal of Advanced Computer Science & Applications*, vol. 16, no. 2, 2025.
- M. A. Siddique *et al.*, "A Multi-Modal Approach for Exploring Sarcoma and Carcinoma Using FTIR and Polarimetric Analysis," *Microscopy Research and Technique*, 2025.
- J. Yang *et al.*, "BrainCNN: Automated Brain Tumor Grading from Magnetic Resonance Images Using a Convolutional Neural Network-Based Customized Model," *SLAS Technology*, p. 100334, 2025.
- I. Njeh *et al.*, "3D multimodal MRI brain glioma tumor and edema segmentation: A graph cut distribution matching approach," *Computerized Medical Imaging and Graphics*, vol. 40, pp. 108-119, 2015.
- A. Farooq *et al.*, "CONCEPTUAL FRAMEWORK FOR AN EEG-DRIVEN HUMAN BRAIN INTERFACE FOR NEURAL ENCODING AND DECODING," *Spectrum of Engineering Sciences*, vol. 4, no. 5, pp. 2419-2435, 2026.
- [83] A. Farooq, H. Shafique, A. Khursheed, A. Saher, S. Ali, and G. Gilanie, "A NON-INVASIVE METHOD FOR BRAIN TUMOR DETECTION USING COMPUTER VISION AND DEEP LEARNING TECHNIQUES," *Spectrum of Engineering Sciences*, vol. 4, no. 6, pp. 2575-2606, 2026.
- M. Iqbal *et al.*, "Automated Identification of Mango Leaf Diseases Using Deep Convolutional Neural Networks," *Polish Journal of Environmental Studies*, 2026.
- A. Khursheed *et al.*, "A SMART HELMET TO DETECT ANOMALIES OF ITS USERS AND ENVIRONMENT," *Spectrum of Engineering Sciences*, vol. 4, no. 6, pp. 399-418, 2026.
- M. Sajid *et al.*, "Internet of Medical Things-Driven Deep Learning Approach for Automated Heart Sound Classification," *IET Biometrics*, vol. 2026, no. 1, p. 3212328, 2026.
- M. Yasir, F. Siddique, F. Andleeb, G. Gilanie, and H. Ullah, "Differentiation of metastatic and primary brain tumor using magnetic resonance imaging," *International Journal of Radiation Research*, vol. 24, no. 1, pp. 259-265, 2026.
- M. Attique *et al.*, "Colorization and automated segmentation of human T2 MR brain images for characterization of soft tissues," *PLoS one*, vol. 7, no. 3, 2012.
- V. G. Jacob and S. Gupta, "Colorization of grayscale images and videos using a semiautomatic approach," in *Image Processing (ICIP), 2009 16th IEEE International Conference on*, 2009, pp. 1653-1656: IEEE.
- Y. Rathore, A. Dhole, R. Giri, and U. Agrawal, "Colorization of gray scale images using fully automated approach," 2010.
- C. Sauvaget, S. Manuel, J.-N. Vittaut, J. Suarez, and V. Boyer, "Segmented images colorization using harmony," in *Signal-Image Technology and Internet-Based Systems (SITIS), 2010 Sixth International Conference on*, 2010, pp. 153-160: IEEE.

- V. Bochko, P. Välisuo, T. M. Alho, S. Sutinen, J. Parkkinen, and J. T. Alander, "Medical image colorization using learning," in *Conference on Colour in Graphics, Imaging, and Vision*, 2010, vol. 2010, no. 1, pp. 70-74: Society for Imaging Science and Technology.
- G. Holland and P. Bottomley, "A colour display technique for NMR imaging," *Journal of physics E: Scientific instruments*, vol. 10, no. 7, p. 714, 1977.
- M. Documentation. (2016, 15 January). *MatLab Documentation*. Available: <http://www.mathworks.com/access/helpdesk/help/techdoc/matlab.shtml>.
- K. L. Weiss, Q. Dong, W. J. Weadock, R. C. Welsh, and G. V. Shah, "Multiparametric Color-encoded Brain MR Imaging in Talairach Space 1," *Radiographics*, vol. 22, no. 2, pp. e3-e3, 2002.
- K. Weiss, S. Stiving, E. Herderick, J. Cornhill, and D. Chakeres, "Hybrid color MR imaging display," *American Journal of Roentgenology*, vol. 149, no. 4, pp. 825-829, 1987.
- M. d. C. V. Hernández, K. J. Ferguson, F. M. Chappell, and J. M. Wardlaw, "New multispectral MRI data fusion technique for white matter lesion segmentation: method and comparison with thresholding in FLAIR images," *European radiology*, vol. 20, no. 7, pp. 1684-1691, 2010.
- D. H. Demirel. Available: <http://faraday.ee.emu.edu.tr/ee583/Lectures/EE%20583-Lecture01.pdf>
- H. M. School. (2016, 23 May 2016). *Harvard Medical School*. Available: (<http://med.harvard.edu/AANLIB/>)
- M. D. Laurence Germond, Chris Taylor, and Catherine Garbay, *A Multi-agent System for MRI Brain Segmentation*.

