

Medical Image Enhancement For Disease Diagnosis

Lukeshwari Sahu¹, Dr. Nidhi Mishra², Rashi Aggarwal³

¹Assistant Professor, Department of Pharmacy, Kalinga University, Raipur, India.

ku.lukeshwarisahu@kalingauniversity.ac.in, 0009-0002-3045-6538

²Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.

ku.nidhimishra@kalingauniversity.ac.in, 0009-0001-9755-7950

³Assistant Professor, New Delhi Institute of Management, New Delhi, India., E-mail: rashi.ndim@gmail.com, <https://orcid.org/0009-0007-1616-448X>

Abstract

These days, medical imaging plays a crucial role in cancer diagnosis. Nevertheless, in order to lower possible dangers during patient picture acquisition, the quality of these medical photographs is usually lowered. Computer-aided diagnosis systems, which employ algorithms to find unusual aspects in medical images, have seen notable advancements recently. In addition to ensuring consistency in the interpretation of images and illnesses, this aids radiologists in increasing diagnostic accuracy. The quality of medical images, the goal data, is a significant factor in determining the performance level that artificial intelligence systems may attain. Nevertheless, medical photographs have a different pixel value range than regular digital images that AI algorithms typically analyse, and using such data for training without discrimination may lead to subpar algorithm performance. In this study, we propose a medical image improvement approach that combines standard digital image processing with medical image processing modules. This scheme's smooth components and strong contrast are intended to enhance medical picture data. To confirm that this approach is effective in improving the performance of a medical picture segmentation algorithm, we conducted experimental experiments.

Keywords: medical image; computer-aided diagnosis systems; image enhancement

1. INTRODUCTION

Numerous scientific domains, including biology and medicine, have made use of image processing; nevertheless, by examining their photographs, researchers can determine if a cell is alive or dead or represent distinct cell kinds based on its textural characteristics. The reliability and consistency of the forecast are severely hampered by the existing methods of microscopic image analysis of the affected area, which rely entirely on a labor-intensive procedure with a limited number of bone samples [1]. Therefore, a new technique that includes several steps, including pre-processing, object representation, feature extraction, classification, and image interpretation, was developed using image processing in a digital system. Computed tomography, X-ray, magnetic resonance imaging, 2-D histology, anatomical regions of interest, implant material, and morphology are some of the most modern automated and customized image processing tools available today [9]. The results of these approaches were therefore helpful for quick quantitative analysis in research and for measuring the integration of implants or new bone formations [2]. It was discovered that these data were repeatable and appeared to be highly accurate. In the last ten years, image processing techniques have been widely used in medical imaging, and scientists have been consistently working in this tiny subject. Many PC-supported image analysis frameworks have been presented in light of the importance of such outcomes for human wellbeing and the challenges associated with applications [3]. Image processing techniques are particularly interesting because they allow for large-scale factual evaluation in addition to conventional eye screening evaluation and are used in both pathology fields: cytology (the study of cells) and histology (the anatomical study of the minute structure of tissues) [13]. By performing the pretreatment step, the picture data can be enhanced and the features that are essential for additional processing can be found. Understanding the image acquisition device is necessary before preprocessing an image, taking into account the items studied in the image as well as the conditions under which the image was taken [4]. The item is represented by the parameters that visualize the structures and quantify anomalies [10].

2. REVIEW OF LITERATURE

These techniques seek to highlight the desired aspects while achieving a thorough improvement of medical images. Furthermore, this study examines and seeks to resolve the root causes of medical picture segmentation's low accuracy. The limited quantity and subpar quality of medical image collections are the primary causes of this low accuracy. The problem of insufficient medical image data is lessened by the Segment Anything Model's Data Engine, which offers a consistent flow of data [5]. This article attempts to use image-enhancement techniques to provide high-quality data in order to increase the accuracy of the model. We primarily provide a combination of generic digital image enhancement techniques and medical image processing technologies to improve the quality of medical images and the precision of segmentation models [6]. Generic enhancement techniques are primarily used for noise reduction and overall contrast improvement, whereas medical image processing techniques concentrate on the tailored processing of specific areas of interest, such as the liver. This study discusses in detail the medical image enhancement strategy's architecture, datasets, data-processing methods, experimental setup, and performance evaluation measures. To appropriately assess the test results, eight metrics are employed, including the Dice coefficient and Intersection over Union (IoU).

3. MATERIALS AND METHODS

The purpose of image enhancement techniques is to improve a picture's visual quality for specific applications by either enhancing or reducing certain aspects of the image [11].

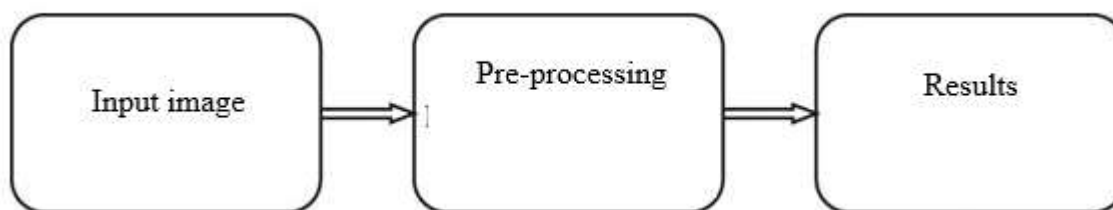


Figure 1: proposed flow

Wavelet de-noising systems use a predetermined threshold value to control wavelet coefficients. By using DWT to the noisy signal, the wavelet coefficients at various scales may be obtained. Generally, the noise causes the coefficients with smaller extents than the threshold value to be replaced by zero, while the input signal essentially creates the coefficients with larger sizes than the pre-established limit and either keeps them (hard-thresholding case) or shrinks them (soft-thresholding case) [7]. The de-noised signal could then be replicated using the wavelet coefficients that followed. Wavelet thresholding, which has the ability to denoise signals, was used to estimate the signal. Hard thresholding is a keep-or-kill technique used in the denoising process that reduces the noise in the image and preserves the necessary information without taking into account the frequency components of the signal [12]. Hard thresholding involves vanishing coefficients that are smaller than the limit and leaving the others unchanged, but it also continuously cycles the scaling to keep the coefficients focused on zero. It has very low frequency characteristics and is entirely composed of different content, which means that the process ultimately yields meaningful information [15]. Badrinarayanan et al. created SegNet by adding pooling layers to the FCN structure in response to the lower resolution of the masks generated by FCN networks [14]. SegNet's completely symmetric architecture enables it to generate an encoder-decoder configuration with convolution-deconvolution and pooling-unpooling layers. However, FCN and SegNet are less successful for medical image segmentation since they just identify individual pixels without taking into consideration the relationships between them. This restriction is successfully addressed by U-Net, which was created especially for medical picture segmentation.

4. RESULT

In order to obtain more accurate segmentation, this study integrates shallow and deep characteristics from medical pictures using skip connections and a U-shaped network structure.

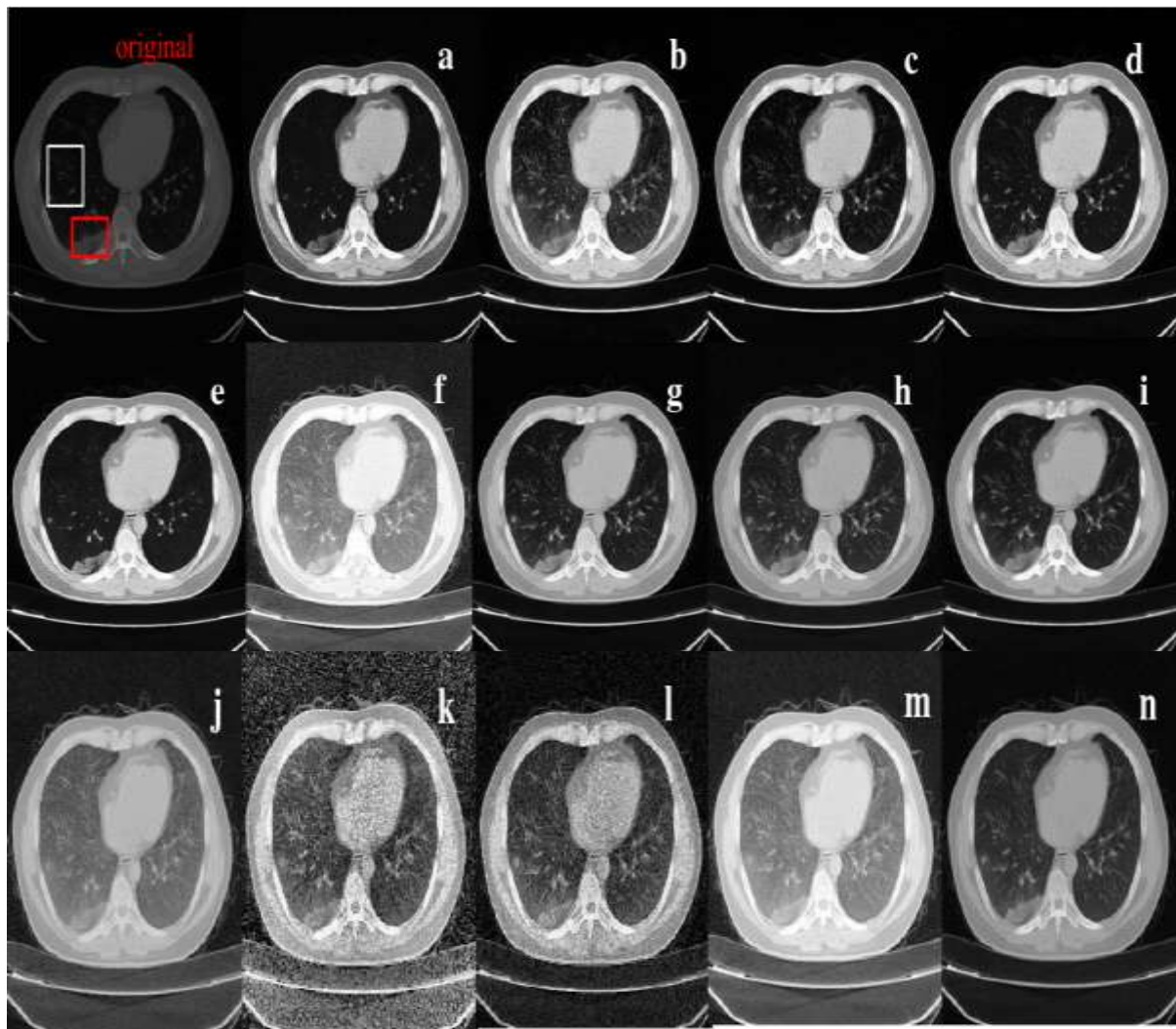
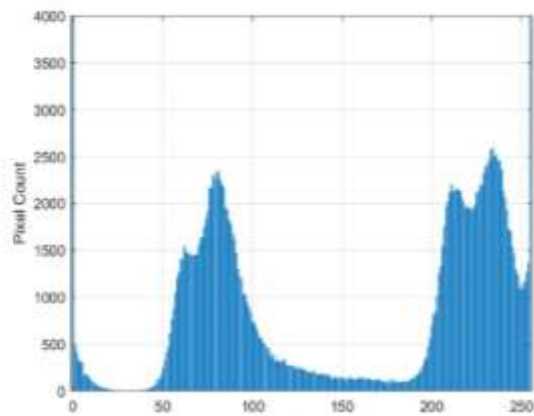


Figure 2: Image enhancement results

The U-Net network, which is widely regarded as the finest algorithm for medical photo segmentation tasks, has been enhanced by numerous researchers. But even adding Transformer design to U-Net hasn't resulted in noticeable speed improvements, particularly when it comes to tumor segmentation tasks, indicating that recent advancements have reached a standstill.



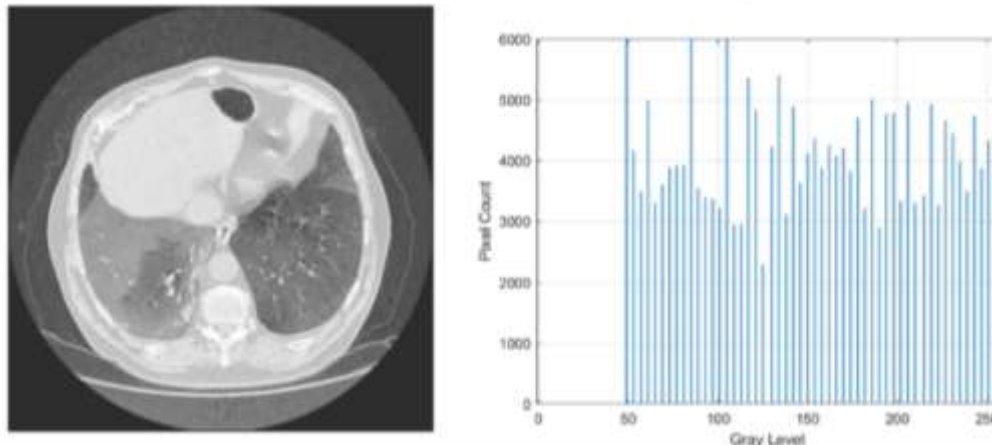


Figure 3: Sample histogram results

By obtaining impressive accuracy in semantic segmentation across nearly all domains, Meta's Segment Anything Model (SAM) has lately demonstrated its powerful segmentation abilities. Researchers have also examined the SAM model's efficacy in the medical domain. In summary, the special qualities of medical images are not sufficiently addressed by existing image enhancing methods. It is feasible to significantly increase their practical utility by incorporating existing medical imaging information into the improvement process while accounting for the unique characteristics of medical jobs. The purpose of this study is to test this theory, with an emphasis on medical image segmentation.

5. CONCLUSION

To sum up, this study offers a fresh method of data preparation created especially for the analysis of medical images. By combining global and local enhancement findings in a weighted way, we were able to get impressive results with less noise and better contrast. The effectiveness of this preprocessing method was assessed through liver segmentation using MedSAM. Six assessment measures obtained optimal values, verifying the suggested methodology. Interestingly, the gains were especially noticeable in the dice coefficient and Intersection over Union (IoU) scores. This shows that the mask produced by the suggested preprocessing technique, which is then followed by MedSAM, has the greatest degree of overlap with the real regions while reducing the number of false-positive results. Achieving high accuracy is crucial in the field of medical picture segmentation because inaccurate segmentation is not very useful. With an accuracy of over 90%, the liver area mask generated by our preprocessing method and MedSAM is extremely suitable for use in clinical diagnostic situations. Overall, the findings are encouraging, suggesting that our research has the potential to support healthcare professionals and enhance patient outcomes in the future.

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