Medical Image Analysis and Diagnosis

Binod Kumar,
Department of Computer Science and Engineering,
Master of Technology, Roll no. 23203006, Email: binodk.cs.23@nitj.ac.in
DR. B. R. Ambedkar National Institute of Technology,
Jalandhar, Punjab

Abstract - A wide range of developments and approaches in the field of medical image processing and analysis are covered in this presentation. It goes over several strategies to improve medical picture diagnostics' precision and interpretability. The significance of crisp and noise-free medical images is emphasised by highlighting pre-processing techniques such image denoising and enhancement. The work presents a number of methods, including the LPG-KPCA technique, that are specifically made to reduce noise while maintaining the quality of local structures.

The creation of models for the diagnosis of breast cancer is noteworthy, especially one new method that makes use of anatomical knowledge to create interpretable representations of features. In order to improve practical applicability, this method attempts to classify ultrasound pictures without depending on predetermined regions of interest (ROI).

This also presents a novel 3D ROC analysis that extends conventional ROC curves to include soft judgements, allowing a more nuanced evaluation in medical diagnosis, as illustrated by the classification of magnetic resonance images. Overall, the development of methods for medical image analysis is highlighted in this thorough overview, which aims to raise the standard of medical imaging technologies' overall effectiveness, interpretability, and diagnostic precision.

Keywords - LPG-KPCA technique, Image Segmentation, image denoising and enhancement.

I. INTRODUCTION

The development of modern medicine has completely changed the healthcare industry, bringing in a time when medical imaging tools like X-ray, CT, MRI, and ultrasound, among others, are crucial to medical diagnostic and treatment decisions [1-3]. Almost 80 percent of the data generated in hospitals today comes from these essential medical image resources. Hospitals have embraced Picture Archiving and Communication Systems (PACS) to handle this massive flood of medical picture data [4]. PACS are becoming more and more common as they progress towards more sophisticated regional-level PACS.

This work attempts to solve an urgent requirement for effective structure and management of large and varied medical picture resources in the context of regional PACS systems. This work explores key technologies such as semantic annotation, visual feature library construction, and multi-pattern retrieval [5] and delves into the design of retrieval patterns with a focus on the practical application of modern regional PACS in auxiliary clinical diagnosis, teaching, scientific research, and remote medical treatment [6].

This study emphasises the critical importance that excellent feature extraction has in the performance and efficiency of subsequent image processing. A thorough examination and synthesis of numerous research studies on medical image analysis techniques are provided. These include state-of-the-art techniques such as feature extraction based on deep learning, dictionary learning, local binary pattern algorithms, Gabor filters, and denoising techniques based on wavelet and curvelet analysis. Furthermore, LPG-KPCA, an improved denoising technique, is presented [6]. It uses non-linear models to handle picture noise while preserving structural integrity. Furthermore, the importance of accurate edge detection and image enhancement in medical imaging is underscored [7]. It also discusses the difficulties caused by various imaging standards and makes the case for the adoption of a single DICOM medical imaging standard. Additionally, it emphasises how important receiver operating characteristic (ROC) analysis [8] is for assessing how effective diagnostic systems are, especially when it comes to radiological image analysis.

This work essentially functions as a thorough synthesis and analysis of cutting-edge approaches, algorithms, and research projects with the goal of advancing medical imaging practises and technology for improved healthcare diagnostics and treatments [10].

Image Processing

The only objective of medical image processing is to increase the contents' interpretability, as opposed to general image processing, which also aims to create art or improve an image's aesthetics [11]. This could entail both the automated or manual extraction of information and an enhancement of the image itself to improve the perception of specific features.

Image enhancement: Image enhancement is the process of improving an image's contours and other pertinent aspects while also removing image distortions like noise and background inhomogeneities.

Image segmentation: Finding the contours of an anatomical structure, such as an organ, a vessel, or a tumour lesion, is known as image segmentation.

Image registration: Image registration is the process of spatially transforming an image so that it perfectly resembles a reference image. For instance, when combining images from various modalities (like PET/CT), this is required.

Quantification: Quantification is the process of determining the physiological or geometrical properties of an anatomical structure, such as tissue composition or perfusion characteristics, or volume, diameter, and curvature [12].

Visualisation: The rendering of image data in two and three dimensions (volume rendering, for example) and virtual models (surface models, for example) of organs and other anatomical structures.

Computer-aided detection: The identification and characterization of pathological structures and lesions, such as tumour lesions or vascular obstructions, with the use of computers.

II. PREVIOUS WORK

In our earlier study, I reviewed various research papers where technology's contribution to the improvement of medical imaging has expanded the field of medical science. Use the captivating tactics to battle more precisely [2][3]. There is ongoing research on various moderns [4] [5] [6] to analyse and enhance the system for medical imaging. In this section, we summarise the previous research works on medical image processing and analysis for nuclear medicine diagnosis [2], microwave medical image segmentation for brain stroke diagnosis [3], and the analysis and design of multi-retrieval of the regional scheme PACS system based on medical images. [6].

III. PROPOSED METHODOLOGY:

A. Object Based Image Processing

The ability of the human mind to recognise intricate patterns in images, make use of past information, and comprehend relationships between objects at different scales is remarkable. But computers can't understand complex structures because they see images as grids of voxels with intensity values. As can be seen in the case of identifying the spine in CT images, traditional voxel-based image processing algorithms perform poorly in situations where distinct intensity values do not define the structures of interest. The spine may appear distorted or indistinct due to a lack of distinct intensity values.

Using programmes such as MeVisLab, object-based image analysis extracts the spectral, shape, and relational properties of objects from images to simulate human vision. For spine detection, an iterative procedure is employed. First, the image is segmented into objects that resemble vertebrae using a watershed-based technique. Then, some objects are identified as putative vertebrae thanks to strict constraints based on spectral and shape properties. Recognising adjacent structures is aided by using relative location in relation to identified vertebrae and previous knowledge that vertebrae align vertically. By progressively identifying the entire spine, even in noisy or lesion-affected images, this iterative process improves detection.

This object-based analysis method allows for a more nuanced understanding of complex structures, outperforming traditional voxel-based approaches. It iteratively refines detection by incorporating prior knowledge about the expected characteristics of structures, enabling robust identification even in challenging image conditions.

B. Medical image processing and analysis for nuclear medicine diagnosis:

The majority of digital radiological modalities, both current and historical, collect imaging data in different ways based on the manufacturer. as a result of applying various standards. Therefore, in order to use imaging data, specific software from each manufacturer of the modalities is required. This makes data exchange between modalities from different manufacturers costly and inconvenient. Additionally, it has reduced the machine's efficiency. These days, radiological modalities from various manufacturers can exchange imaging data by using the DICOM medical imaging standard, which was developed as the industry standard.

DICOM (Digital Imaging and Communication in Medicine) is a standard, which has been developed by ACR/NEMA. The National Electrical Manufacturers Association is known as NEMA, and the American College of Radiology is known as ACR. The equipment from various manufacturers can communicate thanks to this standard. For instance, the header information related to CT images will be in the same format regardless of the manufacturer, and all CT images will be stored in the same format. This also applies to the devices used to create the images. The initial standard concentrated on looking at data between different companies using point-to-point connections. However, the DCOM standard has kept up with the quick development of computer networks, and PACS is currently in use thanks to the idea of network standards controlling information. In many professional fields, adoption of the DICOM standard is required due to its strong adaptability.

C. Microwave Medical Image Segmentation for Brain Stroke Diagnosis:

In order to glean insightful information from medical imaging data, image segmentation techniques are essential. Conventional techniques such as region-growing and thresholding provide a solid basis, but in Microwave Medical Imaging (MMI) the intrinsic uncertainties in the imaging process can reduce their effectiveness. Because DBIM (Distorted Born Iterative Method) produces continuous images, MMI images produced lack sharpness, in contrast to MRI images that have more defined boundaries.

Conventional segmentation techniques are less effective for MMI images due to the non-linear relationships inherent in DBIM, which hinder precise dielectric constant acquisition. While certain segmentation techniques concentrate on differentiating between different tissue types, they ignore uncertainties brought about by the MMI process, which restricts segmentation advancements.

This addresses DBIM-induced uncertainties by introducing a novel technique called Imaging-Process-Informed Image Segmentation (IPI-IS). This technique improves the contrast between haemorrhagic and healthy tissues by incorporating previous knowledge from physiological models. First, the method uses statistical learning to estimate the non-linear relationships caused by DBIM. The picture is then adjusted using this information, resulting in a determination of the dielectric constant that is more precise. By taking into account imaging uncertainties, the IPI-IS method addresses the challenges associated with MMI image segmentation and opens the door to improved segmentation accuracy. Accurate microwave medical image segmentation frequently requires a layer-by-layer approach, especially for complex structures like the brain. N - 1 cycles are needed for this process, assuming the region under examination (RUE) has N layers. Two essential curves are present in every cycle: the sensing curve and the curve, adjusting dynamically to improve the segmentation.

The DBIM (Distorted Born Iterative Method) imaging uncertainty is integrated to derive the sensing curve for a particular layer within the cycle. The relationship between the estimated and actual dielectric constants—obtained using statistical techniques—is represented by this curve. Nevertheless, covering the whole range of dielectric constants may be difficult due to the statistical nature of this curve, particularly with regard to special values.

The adjustment curve, which makes use of the sensing curve and API (Artificial Propagation Intelligence), is presented as a solution to this restriction. The adjustment ratio for the layer is defined by the combination of the sensing curve and the dielectric constant range for the layer, which is determined in part by the API. In situations where the entire range is not covered by the sensing curve, working dynamically to refine the se extrapolation techniques extend the adjustment curve.

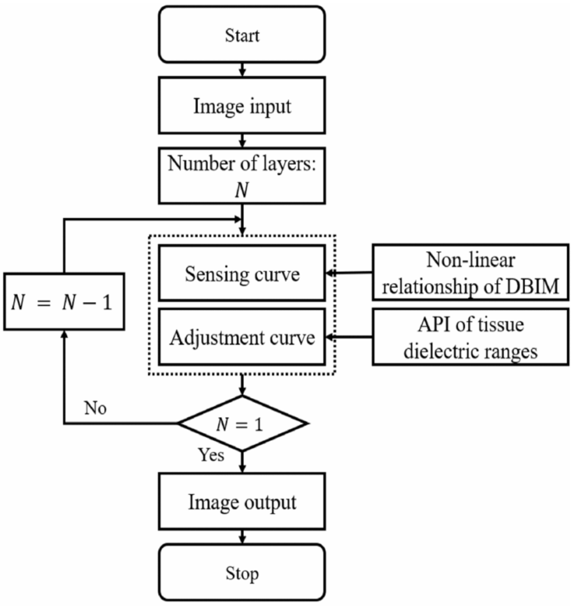

Figure 1: Algorithm Flowchart

D. LPG-KPCA METHOD:

This method's primary goal is to use a kernel trick to reduce noise and improve the local structure of medical images. The suggested block matching-based LPG-KPCA is a non-linear model that performs better than linear models primarily because it concentrates on maintaining the edges. The suggested approach repeats this process once more to suppress any residual noise and preserve the local structure quality of the image, which is significantly better than the current LPG-PCA method.

System Structure:

The three steps of this method are as follows: first, use block matching based local pixel grouping to obtain local similar characteristics; next, use Kernel based PCA transform to identify the non-linear principle components for denoising; and last, use Kernel based Inverse PCA transformation to recover the original dataset from the transformed dataset. Figure 1 illustrates these steps in reducing noise.

The traditional LPG-PCA method was improved upon to create the suggested block matching based LPG-KPCA method. In actuality, LPG-PCA works with linear structures, which makes comparisons with the suggested method very different. Using a sliding window in the image, the block matching concept is used to find similar blocks. Compared to a single pixel, the vector variable suppresses noise more effectively.

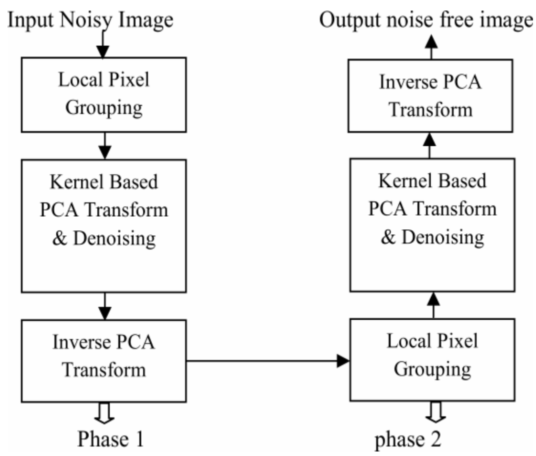

Figure 2: System structure of proposed LPG-KPCA scheme

E. HOPFIELD NEURAL NETWORK:

Hopfield neural network for the optimization application consists of many interconnected neuron elements. Magnetic Resonance Images (MRI) have been segmented using the Hopfield Neural Network (HNN). Although it is promising, it has drawbacks: because the energy landscape it traverses is nonconvex, it frequently finds itself stuck in early local minima. This makes it more difficult for it to arrive at the best image segmentation solutions.

By avoiding an early convergence to local minima, these solutions seek to enable the network to delve deeper into the exploration of the energy landscape. Furthermore, the study found that segmentation accuracy significantly increases with the number of pixel features fed into the network.

Using colour images as an example, we can see that they are multidimensional, with RGB components representing each pixel, just like MRIs. Further information about regions such as the cytoplasm and nucleus, derived from particular chromatic properties, improves segmentation accuracy in the context of colour images of sputum cells.

The result of these developments is more accurate image segmentation, which is essential for image analysis in the diagnosis of lung cancer.

We have applied the RGB components of multiple sputum images to the HNN's input. However, because the number of regions is difficult to estimate in advance, the segmentation is less accurate and cannot be automated due to the extreme variations in the Gray-levels of the images and the relative contrast among nuclei caused by inevitable staining variations among individual cells, the cytoplasm folds, and the debris cells. However, since most quantitative procedures rely on measurements of nuclear features, the most crucial goal in processing cell clusters is the identification and precise segmentation of the nuclei. For this reason, An algorithm for non sputum cell masking using our database of sputum colour images. As soon as these masked pictures are identified, they are supplied to the HNN's input along with a portion of the raw image's RGB components.

IV. CONCLUSION

In summary, the development of medical imaging technologies—which mainly rely on instruments like X-ray, CT, MRI, and ultrasound—has completely transformed healthcare. A wide range of critical areas in medical image processing are covered in this study, including object-based analysis, image enhancement and segmentation, and the integration of cutting-edge methods like Hopfield Neural Networks (HNN) and Imaging-Process-Informed Image Segmentation (IPI-IS).

The review emphasises how crucial it is to implement the DICOM standard in order to enable effective data exchange between different radiological modalities. It also draws attention to the shortcomings of conventional segmentation techniques in microwave medical imaging (MMI) and suggests alternatives, such as IPI-IS, to deal with the inherent uncertainties in MMI image processing.

Additionally, this work explores the potential of HNN for image segmentation in the context of lung cancer diagnosis and presents the LPG-KPCA method, a robust denoising technique that improves image quality by preserving local structures.

This thorough analysis essentially presents a range of approaches and their potential to improve medical imaging procedures. These approaches seek to enhance healthcare treatment outcomes and diagnostic accuracy by tackling image processing challenges.

REFERENCES:

[1] A Homeyer, M. Schwier, and H. K. Hahn, A generic concept for object-based image analysis," in Proc. Int. Conf. Computer Vision Theory and Applications, 2010, pp. 530–533.

[2] Piyamas Suapang, Kobchai Dejhan and Surapun Yimmun, A Medical Image Processing and Analysis for Nuclear Medicine Diagnosis: International Conference on Control, Automation and Systems 2010 Oct. 27-30, 2010 in KINTEX, Gyeonggi-do, Korea.

[3] Chenghui Liu; Zheng Gong; Yifan Chen; Shuaiting Yao, Microwave Medical Image Segmentation for Brain Stroke Diagnosis: 2023 IEEE 17th International Symposium on Medical Information and Communication Technology .

[4] Yanli Wan, Hongpu Hu*, Chen Quan, Minjiang Guo, Yan Wang, Analysis and Design of Multi-retrieval of regional scheme PACS System Based on Medical Images: 2016 8th International Conference on Information Technology in Medicine and Education.

[5] Wu, Sheng Hu, Medical Image Feature Extraction and Visualization based on Principal component analysis: The l0th International Conference on Control, Automation and Information Sciences Xi'an, China - October 14-17, 2021.

[6] T. Gopi Rambabu, K.V. Krishna Kishore , Medical Image Denoising using KPCA with Local Pixel Grouping: 2015 International Conference on Computer Communication and Informatics (ICCCI - 2015), Jan. 08 – 10, 2015, Coimbatore, INDIA.

[7] Shaikh Mahmudul Islam, Himadri Shekhar Mondal, Image Enhancement Based Medical Image Analysis: 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT) Kanpur, India.

[8] Su Wang, Chein Chang Sheng-Chih Yang, Giu-Cheng Hsu: 3D ROC Analysis for Medical Imaging Diagnosis, Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 2005.

[9] Sammouda Rachidl, Noboru Niki, Hiromu Nishitani, S. Nakamura, and S. Mori, Segmentation of sputum colour Image for lung cancer Diagnosis: Proceedings International Conference On Image Processing, Santa Barbara, CA, USA.

[10] Anca Loredana Ion , Stefan Udristoiu, An Experimental Framework for Learning the Medical Image Diagnosis: Proceedings of the ITI 2011 33rd Int. Conf. on Information Technology Interfaces, June 27-30, 2011, Cavtat, Croatia.

[11] Lidia Ogiela1 , Ryszard Tadeusiewicz2 , Marek R. Ogiela2 AGH University of Science and Technology, Cognitive Approach to Medical Pattern Recognition, Structure Modelling and Image Understanding: 2008 International Conference on BioMedical Engineering and Informatics.

[12] Phooi Yee Lau, Shinji Ozawa Ozawa Laboratory, Center for Information, Communication and Media Technologies, Keio University, An image-based analysis for classifying multimodal brain images in the Image-guided Medical Diagnosis Model: Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA September 1-5, 2004.