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An Approach Towards Effective Processing of Liver Tumour Data

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Abstract— **Liver tumour has become one of the life-threatening problems which need to be effectively diagnosed. Accurate detection and segmentation of tumour region is crucial for diagnosis. The major challenge persists with existing procedures lack on false positive values. The objective of the work is to preprocess the Liver CT images effectively in order to derive the images capable of detecting the tumour infected area effectively. The proposed novel work focused on creating an automated liver CT image analysis through image processing technique. The need for effective preprocessing is evaluated here. The study considers MICCAI image dataset for evaluation to have a robust preprocessing framework derived through Boundary extraction algorithm (BEA). The purpose is to extract the region of interest accurately through contour segmentation in order to differentiate the liver structure from the background tissues. To extract the required image intensities highlighted into the extracted region, multi-scaling wavelet transform is applied. The primary challenge of the system is to detect the abnormal pixels present in the input CT images under test, accurately and rapidly. The proposed novel Consistency aware natural looking histogram equalization (CANHE) model is developed to enhance the quality of the input image under test. The presented system comprehensively evaluated to interpret the development of performance measure while integrating the proposed CANHE module and multi-scaling wavelet transform for feature extraction.**

Keywords— Medical imaging, Liver tumour, Image segmentation, Computer vision, Image segmentation.

I. INTRODUCTION

Liver cancer is one of the serious problems of human health resulting in life threatening issues. Liver is one of the vital organs in the human body.[1] The commonly occurring liver tumour problem is hepatocellular carcinoma (HCC) which arises from the basic cell transformation from hepatocytes (the primary cells). Other liver tumour problems include, cholangiocarcinoma and hepatoblastoma are secondary liver tumour issues.[3] The major challenge in the liver tumour disease when not detected in the early stages is metastasize of cells migrate from one place to other regions of the body. in certain cases, the initial cancer originates from other organs such as lungs and breasts and spread over the other regions.[2] The liver tumour spread from other organs of the body is called as metastatic cancer which directly impacts the liver functions. Liver tumour is diagonosed from the computed tomography (CT) images collected from high speed imaging device.[4] Among various liver tumour types, the patients are highly impacted by the HCC. Liver is the primary organ of the human body. Chronic liver diseases impact the occurrence of liver cancer, when it is not treated on time. The long term infections in the liver impact the functionality of the liver and manifest abnormal pattern of liver operations.[5] The clinical tests and various supportive pathological test results such as blood test(BT), liver function test(LFT), blood pressure(BP), temperature(T) are highly helpful to detect the liver tumour in the early stage.[6] The infected HCC spread over the liver tissue, through nodular lines, making the migration of cancer cells more rapidly. Early and accurate detection of liver tumour is important to prevent severe liver corruptions. CT images, MRI images act as the primary source for detection process of liver tumour.[12] During the diagnosis process, unique features are extracted from the liver CT images. Considering the challenges from the existing implementations, towards unique feature extraction not enough to detect the cancer in the early stages, multi-feature model is proposed here. Multi-layer features are important to detect the tumour growth in the early stages.[13] Nodular tumour formations contain fibrous capsules present in the maximum area of the liver that grows deeply into the boundaries of the liver. The false detection of cancer during the single modality-based evaluation is rectified here through multiple modality-based feature models.[14] The required region of interest is developed. During clinical analysis, contrast enhanced CT imaging process improve the quality of detection and support the radiologist to examine the presence of tumour during visual analysis. As the high definition (HD) images of Liver CT increases the processing time during the classification process, the time taken to extract the infected area from the CT images derives more.[15] On the other hand the highly effective classification models such as convolutional neural network(CNN) demands more Graphical processing unit(GPU) which slow down the entire analysis process. A lightweigh architecture is focused to meet the challenges in a effective way. The computational cost in terms of memory towards handling the CNN models are too expensive.[16]

The proposed novel work focused on creating a multi-modality wavelet transform model with CANHE model for enhancing the quality.

The proposed model focused on creating a robust preprocessing model in which the quality of input test images are enhanced through deep analysis of pixel intensities towards abnormal liver and normal liver images.[17]

The performance of the system is evaluated through analysis with preprocessing and analysis without preprocessing etc.

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The rest of the paper is formulated with detailed literature background in Section 2, followed by the system tool selection and deriving constraints for proposed novel method is discussed in Section 3. The methodology is discussed in Section 4. Followed with results and discussions are made.

II. BACKGROUND STUDY

The author explored the method of multi-task attention network(MTANet) utilized for object classification through high quality image processing. The image segmentation through masking of medical object is implemented here.[18] The presented system also tested the reverse attention module in order to segment the given input to get fuse the global background. The architecture is developed with (CNN) Convolutional neural network as the base model, in which attention model is created. The system considers CVC clinical database for segmentation with ISIC 2018 standard skin lesion detection and segmentation database. The presented approach as comparing with the existing state of art approaches, suppose to achieve better accuracy comparing with 25 radiologist direct verification of the tumour diagnosis[7].

The author explored the feature interaction towards multiple channels handling the blocks of down sampling data to eliminate the mis leaded features. A spatially varying fusion mapping technique is utilized to show the lesions accurately. In addition, similarity loss function for evaluating the consistency of data constraints.[19] The presented approach considers PET-CT image having the dataset comparing with multi-modal, multi-channel, cascaded network significantly achieves the higher accuracy value $p<0.05$ with the baseline model[8].

The author explores the multi-phase liver segmentation model utilized to evaluate challenges in the existing state of art concepts such as multi-phase channel added dual attention module seamlessly integrated with multi-scale architecture. The presented system captures required semantic network-based segmentation model keeping feature extraction capability. Scaled weighted loss function is derived to facilitate the amount of false positive functions in segmentation process takes place. The proposed framework makes quantitative and qualitative analysis highlighting the performance of the proposed attention model and over head all feasible challenges happened in mitigation of false positive rate[9].

The author explored the automatic liver tumour segmentation model in which the key role of radiation theraphy for hepatocellular carcinoma(HCC) is considered. The presented system with novel densely connected CT images are considered for analysys, where the dense interconnected network ensure the maximum flow of information between the encoder layers. The method is highly supportive to extract liver tumour features using CC-DenseUNet with LiTS dataset. The standard LiTS dataset contains 20 CT image volumes, 3DIRCADb dataset is compared with performance. The system is experimentally evaluated through proposed clinical dataset and evaluate the performance measure by demonstrating the proposed method with labelled CT images.[10]

The author explored the novel approach towards convolutional neural network (CNN) based liver tumour segmentation using contour segmentation. It consists of CT images of liver with image level labels range from 1 to 8 indicating the specific region of the liver. The proposed model with ContourNet segment the annotation with pixel wise analysis and supervise the segmentation model into two components.[20] An inpainting network with contour segmentation masks, which handle the tumour area present in the pathological images. The segmentation process includes the diffenec finding between the healthy pathology images, and un-healthy pathology images to make effective tumour segmentation. The presented approach is demonstrated and compared with existing state of art approaches in terms of less annotation effort.[11]

III.SYSTEM DESIGN

The existing challenges of liver tumour segmentation relies on frequent occurrence of false positive rates during the classification process. The increased processing space towards graphical processing unit (GPU) when handling large dataset images from different dataset using Convolutional neural network (CNN) is considered. To mitigate the existing issues, the proposed model is developed in focus with preprocessing part with extra effort and scalability. The feaure extraction process need to be tuned to reduce the GPU space utilization, as well as the features need to be in deep to make accurate classification. Keeping the existing constrains, the mitigation process is derived through novel methodologies namely, Boundary extraction algorithm (BEA), Multi-scaling wavelet transform (MSWT), intensity mapping method through Consistency aware natural looking histogram equalization (CANHE) is developed.

IV. METHODOLOGY

A. System architecture

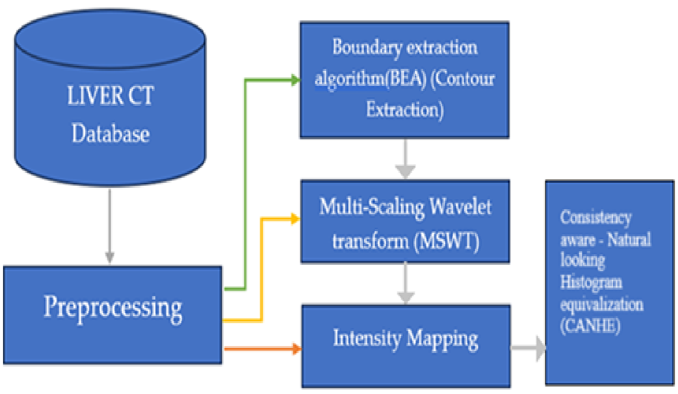


Fig 1. Proposed preprocessing model

Fig 1. Shows the Proposed preprocessing model for the input MICCIA Liver tumour dataset.

A. Implementation Summary

The implementation of Liver CT image analysis through preprocessing part is developed here using MICCAI dataset. The images collected from the standard dataset are common in size. The pre-processed images are tested for dimensional similarity before processing. The dimensions are altered by scaling the image size. MATLAB software is utilized for advanced image processing. The image is preprocessed with boundary extraction algorithm (BEA), feature extracted through multi-scaling wavelet transform, and enhancement of image through CANHE , a novel consistency aware natural looking histogram equalization algorithm is utilized.

The basic image handling process are implemented with singular commands using MATLAB image processing toolbox. The detailed exploration of three step preprocessing (3SPP) method is explained below with necessary mathematical derivations.

B. Boundary extraction algorithm (BEA)

The boundary extraction algorithm (BEA) is derived through edge detection process, where Sobel edge detection and Canny edge detection is developed and let the Chan vase segmentation to happen. The extraction of liver part from the background using texture and structural detailing process. The boundary extraction using contour segmentation is evaluated through the expression below.

$$E(C)= \mu.L(C)+ \lambda^1 \int |I(x,y)-C_1|^2 dxdy+ \lambda^2 \int |I(x,y)-C_2|^2 dxdy \quad (1)$$

Where C act as the contour of the image

μ defines the controls for smoothening process of the segmented region

$\lambda 1$ and $\lambda 2$ determines the homogeneity of control region

C1 and C2 represents the average intensities of the contour region

The Chan-Vese model is a region-based image segmentation process which considers energy minimization for accurate segmentation of boundary of the object with classified with weak edge and poor edge. The region of interest is extracted from the background tissue part. The energy function of the BEA consists of multiple terms such as μ which denotes the smoothness of the structure. The region of interest (ROI) for the given image extracts the foreground as liver area, and the background as tissue area. The region homogeneity constrains are represented by $\lambda 1$ and $\lambda 2$ which balance the similarity of pixel intensities within the extracted region. Traditional method of image segmentation fail in certain extent when extracting the region from the background due to low quality image, blur image, occluded image regions. The conventional edge detection is not enough to extract the region of interest accurately, perhaps the global intensity information needs more deep insights towards the robust segmentation process which improves the precision of tumour segmentation.

C. Multi-Scaling Wavelet Transform

The Multi-Scaling Wavelet Transform (MSWT) is considered as one of the robust methods for extracting the dynamically changing pixel intensities. In Multi-resolution decomposition process, the image data is broken into different levels of frequency component acquiring both the large scale structures appropriately. The process is more precise for effective medial image processing such as Liver CT scan analysis, detection of small objects in the CT images, detection of abnormal pixel intensities during the mapping process and essential for abnormalities detection.

D. Key Concept of MSWT

The wavelet transform is derived from traditional Fourier transform (FFT) method using localized wavelet coefficients to adopt dynamically varying scale. Instead of analysing the image region in single modality, MSWT is often utilized with smooth frequency regions and structural components. The mathematical expressions utilized for the MSWT of the input image pixel intensity values are shown below.

$$W(a,b) = \int f(t)\, \psi_{a,b}(t)\, dt \quad (2)$$

Where, $\psi a,b$ (t) denotes the wavelet function,

a is the variable act as the scaling factor (controls the resolution of the images)

b represents the translational factor which shift the wavelet.

For unique discrete inputs from the images such as Discrete wavelet transform (DWT), the image values are decomposed into coefficients for detailing and approximation.

$$A_j = \sum x(n)\, \phi_{j,n} \quad (3)$$
$$D_j = \sum x(n)\, \psi_{j,n} \quad (4)$$

Where A_j denotes the smooth structure extraction coefficient through low-frequency approximation

D_j represents the edges and high frequency textures

In the proposed liver CT image analysis, the MSWT model is utilized to enhance the contrast and reduce the noise part allowing the image region of interest, detect the edges fine tune the structural parts allowing the region of interest from the CT images get highlighted in the process. To proposed approach improves the dimensionality altered features for analysis.

In order to evaluate the maximum benefit of a proposed model, it is required to assess both the performance metrics such as accuracy and precision during the evaluation process. The amount of error occurs at the initial processing of the proposed model till the end of the proposed model is important to evaluate the loss parameter. The loss of the proposed model kept decreasing, hence the level of accuracy starts increasing.

V. RESULTS AND DISCUSSIONS

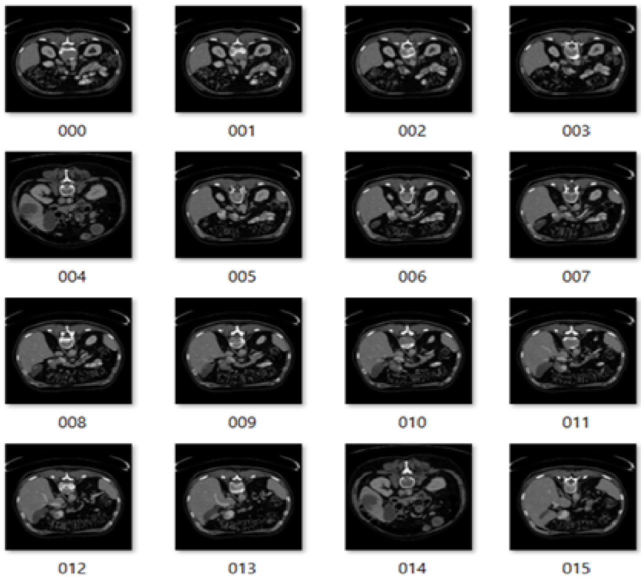


Fig 2. Input test dataset MICCIA

Fig 2. Shows the input test dataset collected from MICCIA. The random samples of images are visualized here to show case the quality of input images under test. The images are high quality and have good resolution. The images are different size and labelled. The images are kept in the linear labelled files read directly from the image database. The images are collected from standard dataset portal further required to be compared with the real time tumor images.

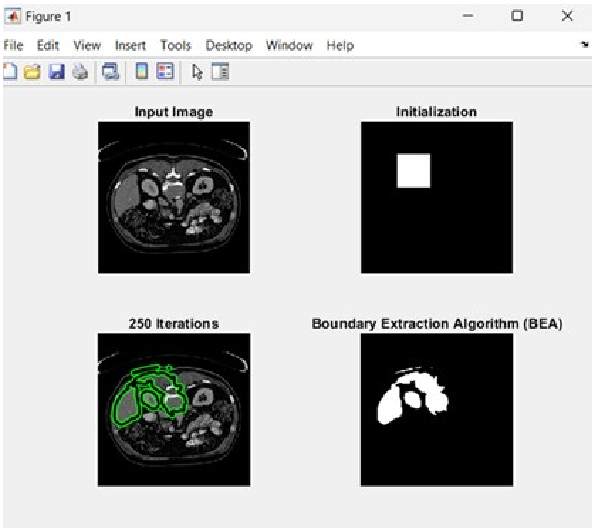


Fig 3. BEA results

Fig 2. Shows the input test dataset collected from MICCIA and applied to BEA. The region of interest (ROI) from the whole liver CT images are extracted from the background tissues. The highlighted part of the liver is further utilized for feature extraction and intensity mapping through MSWT.The initial position of the image segmentation par start with a small square shaped pixel area where the dimentions are fixed in size. From the initial position of the pixels, the region started growing and extract the affected area that differs from normal region.

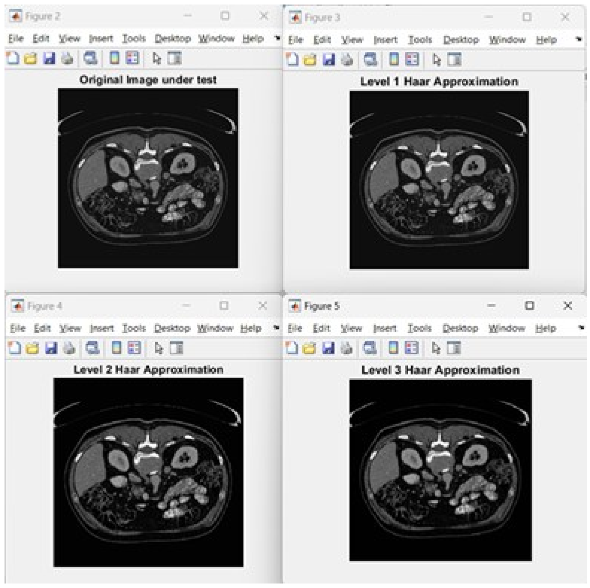


Fig 4. Multi-Scale Wavelet transform (MSWT)

Fig 4. Shows the results of Multi-Scale Wavelet transform (MSWT) for image normalization. The normalized images are utilized for mapping the unique intensity mapping. The intensities of the CT image act as the primary input for tumor analysis. The results depict the different levels of Haar wavelet transforms performed with the input test images and the filtering levels can be increased to achieve better accuracy and resolution.

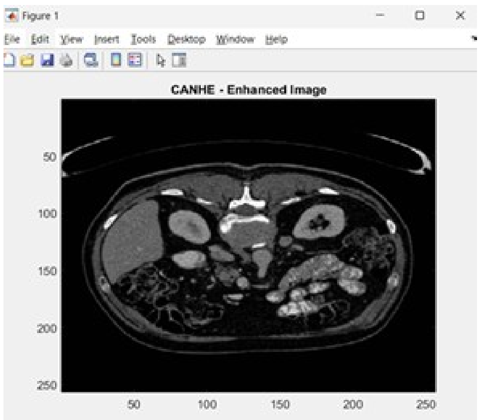


Fig 5. CANHE – enhanced image

Fig 5. presents the Consistency-Aware Natural-Looking Histogram Equalization (CANHE) enhanced image, showing the significant development in image clarity. Conventional histogram equalization increases the contrast, unlike the existing method, here the proposed CANHE model works deep towards the pixel intensities and enhance the patches to detect the critical part of the liver CT images. The highlighted images with improved resolution, improved brightness evaluate to tackle the challenges in classification process. The enhanced image often helpful to differentiate the normal tissue and abnormal tissue present in the medical images.

Table 1. Pre-processed image specifications

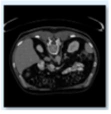
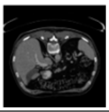
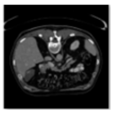
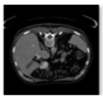
Input Image size	MSE of original image	Histogram equivalized image	MSE of Histogram equivalized image
	0.1245		0.102
	0.4521		0.147
	0.8865		0.112
	0.4785		0.201

Table 1. shows the preprocessing image of the specified test image before CANHE model and after the CANHE model for enhanced image. The specific image is evaluated through mean square error(MSE). The MSE is evaluated by the formula,

$$MSE= 1/m\sum (i=0) \sum(j=0) [I(i,j)-K(i,j)]^2 \quad (5)$$

The Eqn (5). shows the MSE of the proposed CANHE processed image. The original image and enhanced image MSE value is depicted in the **Table 1.**

VI. CONCLUSION

Liver tumor has become one of the life-threatening problems for humans, faces serious challenges in these days. The need for effective liver tumor segmentations algorithms that produce less complex architecture, reduced memory space in the computing environment is important. The proposed framework started as the initiative for effective detection and evaluation of Liver CT images before fetching the data into classification unit. The proposed method considers the existing challenges and developed the preprocessing model for data cleaning and normalization. The main issue still exists with the current procedures' inability to detect false positive results. Mitigation of false positive rate is important to increase the quality of classification process. For evaluation, the paper uses the MICCAI image dataset, which has a strong preprocessing framework built from the boundary extraction algorithm (BEA). The goal is to distinguish the liver structure from the surrounding tissues by precisely extracting the region of interest using contour segmentation. Multi-scaling wavelet transform is used to extract the necessary picture intensities emphasized into the extracted region. The system's main task is to quickly and precisely identify any aberrant pixels in the input CT images that are being tested. To improve the quality of the input image being tested, a novel Consistency aware natural looking histogram equalization (CANHE) model has been proposed. The image enhancement is done and achieved the average MSE of 0.124. The major challenge persist with the proposed architecture in terms of preprocessing, the system relies on the standard dataset, perhaps more such datasets need to be considered for comparative analysis and deep deriving factors towards liver tumor segmentation.

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