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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 590-595 | e-ISSN: 2347-470X

Cancer Symptoms Detection from Liver CT Images Using Multistage Pre-Processors

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ABSTRACT- Visually cancer is the abnormal pattern with predefined structure could be found in liver Computed Tomography (CT) images. Using deep convolution neural network computation and image processing, this detected abnormal pattern cluster can be classified in different liver issue types. Full size liver CT scan images consisting different body parts, and these are ultrasonic based gray scaled image construction. The primary challenge in the cancer symptoms detection process is to extract the liver area out of image then finding out the actual area of abnormality to conclude whether abnormality is cancer or any other issues on liver. This is two stage processes, first is to segment the abnormality area and second is to perform pattern matching to identify the abnormality. This research paper primarily focuses on different pre-processing techniques and stages involved in liver abnormality segmentation.

General Terms: Deep Learning, Medical Image Processing
Keywords: Region of Interest, Deep Learning, Image Segmentation, Machine Learning, Edge Detection, modality, DICOM.

ARTICLE INFORMATION

Author(s): Mohammad Anwarul Siddique, Shailendra Kumar Singh and Moin Hasan;
Received: 23/03/2023; **Accepted**: 13/06/2023; **Published**: 30/06/2023;
e-ISSN: 2347-470X;
Paper Id: IJEER-2023_181;
Citation: 10.37391/IJEER.110247
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110247.html

This article belongs to the Special Issue on **Mobile Computing assisted by Artificial Intelligent for 5G/ 6G/ Radio Communication**

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1. INTRODUCTION

Radiology is the medical discipline that uses medical imaging to diagnose diseases. Diagnostic radiologists use a variety of imaging procedures to see inside the body and assess or diagnose the patient's condition through his knowledge and visual inspection expertise. Different researchers are developing image processing-based computer aided auto inspection methods for identifying the different issues in human body's external and internal parts using different imaging technologies and equipment. This will help in getting faster result in the visual diagnosis process. These methods in the form of firmware needs to reside inside radiology machines called modality and work on predefined format of imaging. This firmware is a special purpose firmware with predefined phases of executions.

Liver issues like cancer, tumor, fungus, or damages are recommended to monitor through radiograph at first level diagnosis as liver is internal part of the body. Cancer is nothing but the transformation of natural liver cells that results in change of volume and the structure of natural liver cells [1]. The cancer cells vary in size, volume and shape from natural cells that aids in identification of cancer cells. Visual liver issues detection is identifying the abnormality on liver if any and then through pattern matching concluding the type of issues like accidental scar, fungus, tissue damage, or the cancer. This result is based in the knowledge and expertise about patterns [2].

Visually every issue has some pattern and making system aware of these patterns is primarily called as model training phase. This training set as an input to the pattern matching algorithm could be a manually hard coded definition, independent manually prepared input definition file based, or the automatic training set built using sample input collection. Manually hard coded technique is very complex and requires lot of time and expertise and thus not used very frequently. Proposed technique is an example of manually prepared input definition file based technique. Models trained using existing neural network architectures such U-Net is an example of automatic training using sample data [3].

Radio imaging techniques such as Computed Tomography (CT) images, Ultrasonic images, and Positron Emission Tomography (PET) images are used to detect anomalies in any part of the body [4]. Due to ease of capturing inner details of human body, less time required and low cost, CT images have become very popular imaging technique [5]. Capturing liver image is a very

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difficult task due to its placement in human body. Also, shape and size of liver differs from person to person. It is different even for male and female [6]. The liver cancer causes structural, shape and intensity changes in the liver images which can be used to distinguish between normal and cancerous liver image [7]. CT scan is rapid technique of image acquisition, and it can provide the images of organs, skeletal structure, and tissues. Due to variable size and shape of liver, and its placement with other organs, Liver CT images cannot be directly used for cancer detection [8].

Deep convolutional neural network (DCNN) model is designed and trained to identify or detect the specified pattern inside given input cluster and conclude the result visually, textually, or numerically. These patterns could be a text block, pixel patterned cluster, sound graph, digital signals, or the analog signals. Any CNN model is trained to identify the object in input, so for image processing-based object detection or to train the DCNN model, system needs actual shape, object, pattern, or the cluster of the actual object to detect [9]. Different researchers and developers are using whole CT image to train the model, however whole image cannot be considered for detection of abnormality patch in CT image. Hence the first challenge for liver abnormalities detection is to be extracting the abnormality area or region of interest.

The remaining research paper have following sections. *Section 2* explains related work in medical imaging. The explanation of proposed solution is given in *section 3*. Experimental results are presented in *section 4* and *section 5* concludes this article.

2. RELATED WORK

2.1 Structural Definition of Cancer

Typically, two categories of liver cancer are: *(i)* benign liver cancer, categorised as (hepatocellular adenoma, haemangioma, cyst); *(ii)* malignant liver cancer, categorised as (hepatocellular carcinoma, metastasis, and hepatoblastoma), as shown in *figure 1*.

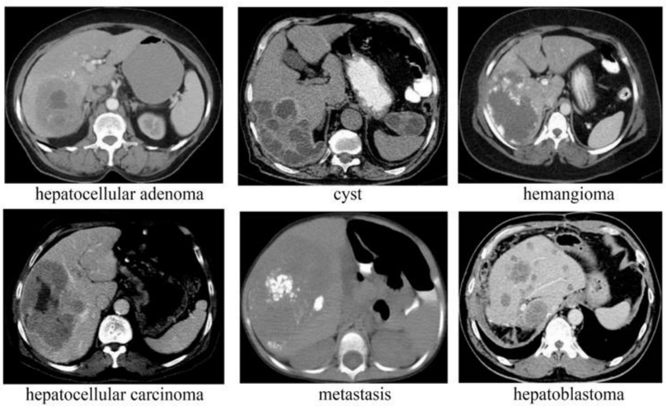

Figure 1: CT images of various types of cancers

Based on the collected liver cancer CT images and based on the discussion with medical expert there are few common patterns with slight changes in abnormality. These sample patterns can be utilized for model training. Patterns of abnormality area only and not the whole CT images. Abnormalities on liver are primarily appeared like fungus shape, oval or circular shape, multi branch spread tree like structure, or distributed multiple patches. For this research medical images were obtained from Life Line Multi Specialty Hospital, Nagpur. Total 200 DICOM images including normal images (images without any abnormality) and images with various abnormalities were provided.

2.2 Medical Imaging

Medical imaging is a technique and a procedure for capturing images of the inside of a person for use in clinical analysis, medical intervention, and the physiology of certain organs or tissues. Medical imaging aims to identify and cure disease as well as disclose internal structures that are covered by the skin and bones. In order to detect anomalies, medical imaging also creates a database of typical anatomy and physiology. The industry standard for managing and communicating data linked to medical imaging is called Digital Imaging and Communications in Medicine (DICOM). The most used format for storing and transferring medical images is DICOM, which enables the integration of equipment used in medical imaging, including scanners, servers, workstations, printers, network gear, and picture archiving and management software.

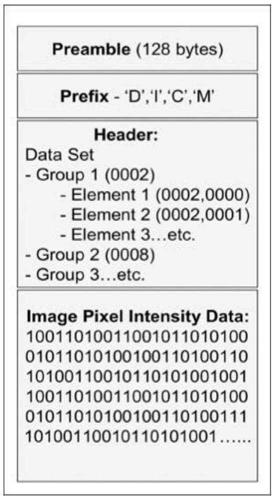

Figure 2: DICOM file structure

As illustrated in *figure 2*, DICOM files are made up of a preamble, a prefix, a header, and a body. They encode two types of information, key/value metadata and pixel intensities, just like JPEG and PNG files do. The header and body of the file are its two most crucial sections. The header includes a variety of other information as well as patient-specific metadata, acquisition settings, dimensions, matrix size, colour space, and encoding. Part 10 of the DICOM standard outlines the organisation, encodings, and representations of these values, which are referred to as "standard data elements" (tags). The development of user-defined (or private) tags is another feature offered by DICOM.

The file's body houses the image data as a single attribute (7FE0) that holds all of the pixel intensities. The header's metadata is used to rebuild the picture data from the binary string's structure (zeroes and ones). DICOM is a very versatile data format that can handle a wide variety of data. The data element of a file may therefore encode numerous frames of a study, a cine (movie) loop, another file (such as a text, PDF, or Word document carrying an imaging report), or 3D files like CAD or OBJ even though it is typically only a single image.

2.3 Computer-vision Cancer Detection Techniques

Before performing any kind of computer vision-based experiments on medical images, it needs to convert into computer vision algorithm required input format. DICOM images having advantages of same size, resolutions, and colour scheme every time makes it easy for algorithms to reduce time on pre-processing and input enhancement. Typically, every image processing algorithm, based on the definition of the action, process, filter, or the detection of object, shape, or pattern. How generic input is provided to algorithm decides the accuracy and performance of the result. Based on the study and available methods we categorized these methods of input in following three categories.

2.3.1 Manual & hard coded

In this case algorithm or the source code are structured to identify the object in image based on the predefined or known generic definition of the object. These algorithms required no extra input, but these are limited to multiple objects. Basic operations like colour, shapes, cluster count, etc. can be performed using this method. For example, detecting cluster of input cluster can be directly extracted using basic pixel colour detection function in any image processing toolbox or library function set. With expertise and fine tuning of calibration values which are affecting the algorithm processing, can achieve high performance results. With very specific dimensional co-ordination and colour scheme identification liver cancer can be detected using this method.

2.3.2 HAAR cascade classifier

A Haar-cascade Classifier can be trained to recognise a variety of items, including handwritten numbers, medical images and various physical structures such automobiles, bikes, fruits, etc. The cascading window is used by Haar cascade, which tries to compute features in each window and determine whether it might be an object, to learn more about how it operates [14]. In a detection window, a Haar feature is effectively the result of calculations on adjacent rectangular sections. In order to calculate the difference between the sums, the pixel intensities in each region must first be added together. A Liver Cancer Pattern Haar Cascade File can be developed using above mentioned method and can be used in future to classify medical images into normal and cancer images.

2.3.3 ML with data collection

Deep Learning is a device learning approach used to build artificial intelligence (AI) systems. It's far based totally at the idea of synthetic neural networks (ANN), designed to perform complex analysis of big quantities of statistics by means of passing it thru more than one layers of neurons. There is a huge kind of deep neural networks (DNN) [13]. Deep convolutional neural networks (CNN or DCNN) are the sort maximum typically used to become aware of patterns in pics and video. DCNN have advanced from conventional synthetic neural networks, the usage of a three-dimensional neural pattern stimulated by using the visible cortex of humans. Deep convolutional neural networks are specially focused on packages like item detection, image classification, recommendation structures, and also are from time to time used for natural language processing. This technique is primarily based on the model education through pattern sample (photograph, video, signals, or textual content) as an input. [10].

3. PROPOSED APPROACH

Based on the on the study and literature survey we proposed a pre-processor stage before sending the input image for cancer detection to DCNN. These stages play major role in accuracy and performance enhancement of the final result. These stages are further explained in detail and illustrated in *figure 3*.

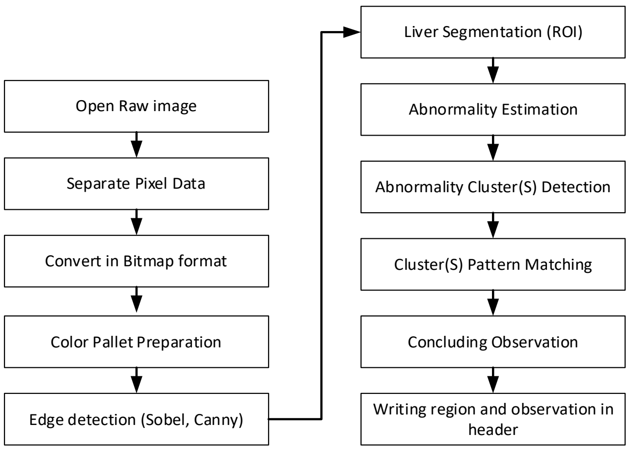

Figure 3: Proposed methodology system flow

Step 1 - DICOM parsing: In this first step system open raw DICOM image and parse the file in to pixel data and the header data. As DICOM file cannot be directly send for image processing as it won't match the pixel and bit format of the images. Separate the pixel data from DICOM file and prepare it for the image conversion. As system extracted pixel data from DICOM file it need to convert in bitmap with RGB bit format. Convert the pixel data in to bitmap file as proposed system primarily deal with bitmap format images only.

Step 2 - Preparing colour pallet: Next step is to extract the colour pallet from converted bitmap image to understand the different colour shades in the image. This is most important step as it output the percentage of different colour level with colour code in the image. Now these colour codes further utilized by flood fill algorithm and segmentation algorithm for accurate segmentation.

In computer graphics, colour quantization, also known as colour image quantization or colour space quantization, is quantization applied to colour spaces. It is a process that lowers the number of distinct colours used in an image, usually with the goal of making the new image look as similar to the original as possible. When displaying images with numerous colours on devices that can only display a finite number of colours, generally due to

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memory limitations, colour quantization is required in order to successfully compress particular types of photographs. The terms "colour quantization" are mostly used in computer graphics research literature; in applications, words like "optimised palette generation," "optimal palette generation," or "reducing colour depth" are used. Some of these are deceptive because the palettes produced by common algorithms aren't always the greatest.

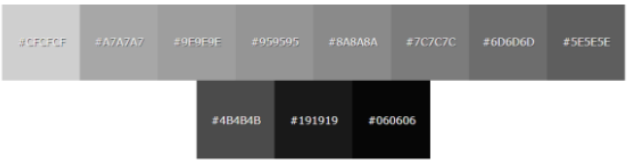


Figure 4: Image colour pallet generation

As seen in *figure 4*, a colour palette with various colour intensities was used to create the image. Here, in addition to recognising the colour level, it also identifies the proportion of each unique colour. Based on the research and observations, it has been determined that the liver is the major component in any DICOM image of a liver, and that this colour code can be used as an input colour code for liver segmentation.

Step 3 - Edge detection: System need to process the edge detection algorithm to in order to enhance segmentation process accuracy. Before segmentation to take place, system need right edges from the image. Based on the boundary and the differences in the colour level or colour shades system detects the area or segment the area in image [10]. This segmentation has multiple input cluster size as shown in result *figure 5*.

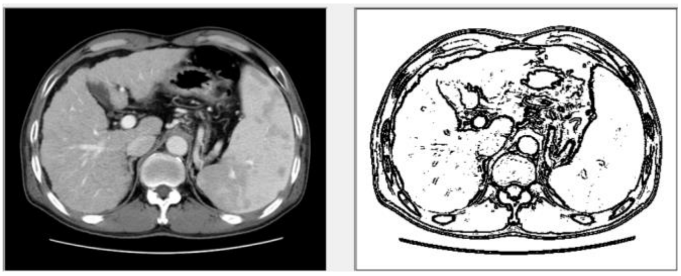
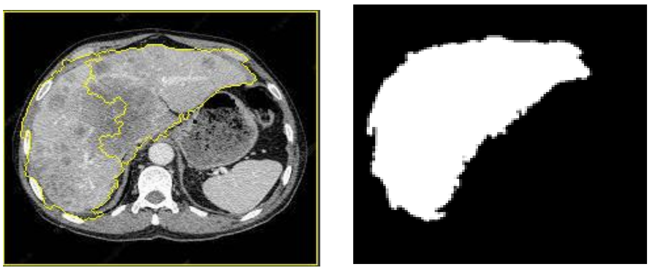


Figure 5: Canny edge detection result

The proposed system used a canny edge detection algorithm**.** The Canny operator works in a multi-stage process. First of all the image is smoothed by Gaussian convolution.

The image is then smoothed to emphasis areas with high first spatial derivatives using a straightforward 2-D first derivative operator. In the image of the gradient magnitude, edges give birth to ridges. Non-maximal suppression is the method by which the algorithm tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top in order to produce a thin line in the output. Two thresholds, T1 and T2, that are T1 > T2, regulate the hysteresis of the tracking process. Only at a position on a ridge higher than T1 may tracking start. From there, tracking continues in both directions until the height of the ridge drops below T2. This hysteresis helps to ensure that noisy edges are not broken up into multiple edge fragments.

Step 4 – Liver segmentation: **Perform the liver segmentation process in order to get the desired region of interest.** Before final stage of pattern-matching, system performs the segmentation operation in order to get the region of interest (ROI). Segmentation is performed based on the cluster building size and k-means algorithm is implemented in the process. In medical images, segmentation is bit difficult as multiple parts with similar colour level and the pattern.



(a) (b)

Figure 6: Liver segmentation in the form of polygon region,
a) Edge detected ridge lines b) Segmented liver area

The unsupervised K-Means clustering algorithm is used to separate the interest area from the background. The given data is clustered or divided into K-clusters or sections based on the K-centroids [11]. The sum of squared distances between all locations and the cluster centre must be kept to a minimum when using K-Means clustering.

K-Means algorithm flow:
1. Choose the number of clusters K. The value of K here needs to be equal of that provided in colour pallet preparation process.
2. To prepare for the clustering, choose K randomly chosen points as the centroids across the image.
3. Assign each data point to the K clusters' nearest centroid.
4. Determine and set each cluster's new centroid.
5. Assign each data point to the new centroid that is closest to it. if there is a transfer. if so, move on to step 4; if not, the model is complete.

Step 5– Abnormality estimation: Before performing the pattern matching on abnormality patch the abnormality estimation is important to understand the area of damage or the abnormality. Separate out the abnormality cluster by detecting the region is the major challenge, as it is nested process start with segmenting the liver area and then performs the abnormality segmentation. Different stages performed may need to repeat for abnormality segmentation also. Here we proposed to perform second level colour cluster segmentation to extract the abnormality pattern as shown in *figure 5*.

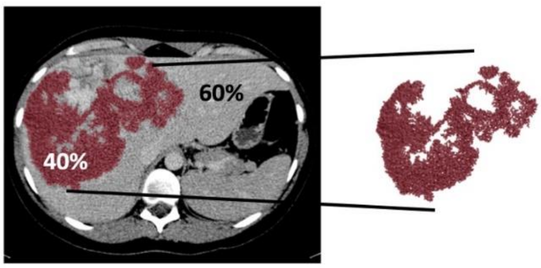


Figure 7: Abnormality estimation from Cancer CT image

Concluding the abnormality, is two-step process where first is to calculate the size of the abnormality cluster to understand its spread and percentages, second step is to conclude the type of abnormality into cancer, tumour, fungus, or the swelling based on the pattern definition or the input training set. Abnormality extraction is the final step in liver cancer detection where binary image and masked image of liver abnormality patch prepared for final input to send through deep convolution neural network for detecting the liver cancer.

Different researchers are proposing the liver detection through training the model using full size liver CT scan image, however this problem statement is to detect the cancer on liver through visual inspection and not comparing whole image. For model training only abnormality patch needs to be providing as a input to the system. All these proposed steps are to find out the actual patch to compare and this process will enhance the accuracy and the performance of the DCNN, as after pre-processing steps processing load to the system will be reduced to extreme extent.

As stated, and described the pre-processing steps involved into liver cancer detection using image processing till abnormality segmentation, there will be multiple patterns matching and result generation stages takes place. *Figure 8* describes the proposed and sequenced stages of execution and result conclusion. For cancer detection pattern would be differed and not exact same every time, hence system must have knowledge base for comparison matrix. Here for pattern matching system needs to go from different machine learning phases and deep learning method [12]. Again, as shown in *figure 8* upon detection of abnormality we are proposing three different model for training to understand and detect the type of abnormality into *(1)*. Cancer, *(2)*. Fungus, and *(3)*. Tumor. Once the system concludes the abnormality is cancer, the abnormality would be having different property like size or its spread pattern like *(1)*. Continues cluster, *(2)*. Distributed even cluster, and *(3)*. Distributed odd cluster as shown in *figure 9*. Upon detecting these properties and the spread structure of cancer, system can detect the different stages of cancer to identify the severity rate of the cancer.

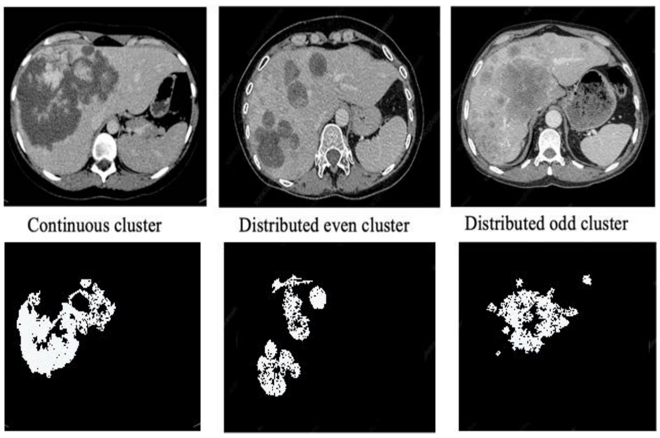


Figure 8: Input masked images for model training

Since we are suggesting the complete model working for DICOM image and file format we recommend writing the result back into DICOM format so that radiology imaging equipment or the machine. Following are the stages involved in the process including result generation.

Step 1: Perform the deep neural network processing for abnormality cluster detected to understand the type of the abnormality.
Step 2: Generate the result based on the pattern matching processing.
Step 3: Writing the result and the observation in the DICOM header file.

4. RESULTS

In order to evaluate the performance of proposed method we have used following criteria. For Segmentation we have used Dice Score (DS), Relative volume Difference (RVD), Volume overlapping error (VOE) and Jacquard Index (JI). For Classification we have used Accuracy, Sensitivity, Specificity, F1 score, Precision and Recall Value. Below tables present our findings. *Table1* presents the result of segmentation and *table 2* presents the results of classification. Both the tables also consist the findings and comparison of proposed method with other state of the art methods.

Table 1: Comparison of Proposed segmentation method with state of the art

Author	DS	VOE	JI	RVD	Dataset
Cho et. al.(2022)	.97	.134	.923	.134	MRI
Menegotto et. al. (2021)	.89	.18	.885	.104	MRI
Zhen et. al.(2020)	.94	.235	.935	.095	CT
Proposed Method	.98	.126	.964	.08	CT

Table 1 presents the result of segmentation on MRI and CT dataset and as seen in above table proposed method achieves better segmentation results.

Table 2: Comparison of Proposed segmentation method with state of the art

Author	Method	Data Set	Accuracy	Sensitivity	Specificity	F1 score
Cho et. al.(2022)	CNN	MRI	86%	90%	87%	87%
Menegotto et. al. (2021)	CNN	MRI	86.9%	NA	NA	86.7%
Bousabarah et. al.(2020)	DCNN	MRI	88%	91%	95%	86.7%
Zhen et. al.(2020)	CNN	CT	94.6%	95%	97.9%	NA
Hamm et. al. (2019)	CNN	MRI	92%	92%	98%	NA
Proposed Method	DCNN	CT	99%	97%	99%	96%

5. CONCLUSION

The research study and observations in the paper primarily focused on present the most important role of every pre-processing stage in liver cancer patch detection. It also states that using nested segmentation process for first liver and second abnormal cluster improve the detection accuracy and enhance the performance of the liver cancer detection process. As we can see from *table 1 and table 2*, proposed method achieved significantly better result for the metrics used for evaluation of performance. An accuracy of 99% was achieved for preprocessed and segmented liver images.

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