



Liver Tumour Detection in Computed Tomography Images Through Image Processing and Deep Learning

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Abstract. This work presents detection of liver tumours in computed tomography (CT) images based on image processing and deep learning. The existing systems for liver tumour detection are based upon support vector machine (SVM) and random forest approach, which are less interpretable, computationally expensive, and require more parameters. The proposed approach commences with a comprehensive pre-processing stage encompassing resizing, histogram equalization, and bilateral filtering for noise reduction. In addition, K-Means image-based segmentation has been employed to extract the CT images' features effectively. The pivotal element of this approach is based on the utilization of convolutional neural networks (CNNs), a potent deep learning tool, to achieve accurate tumour identification by classifying them as benign or malignant. By capitalizing on the strengths of deep learning, specifically CNNs, this method aims to significantly elevate the precision of liver tumour detection within CT scans.

Keywords: Liver tumour · computed tomography · convolution neural network · deep learning

1 Introduction

The liver plays a critical role in numerous vital functions, from processing nutrients to filtering toxins and producing essential proteins [1, 2]. However, uncontrolled growth within the liver can lead to the formation of tumours [3]. These tumours can be either benign (meaning non-cancerous), or malignant, indicating their cancerous nature. If left undetected, malignant liver tumours can progress to liver cancer.

Liver cancer represents a significant global health burden, with estimates suggesting over 800,000 new cases diagnosed annually worldwide. This translates to a devastating impact, claiming the lives of more than 700,000 people each year [4]. Early detection is crucial for improving patient outcomes, as liver tumours can often grow undetected in

their early stages. Traditional diagnostic methods have limitations in identifying these small tumours, highlighting the need for more accurate and sensitive tools. Early and accurate diagnosis plays a critical role in successful liver tumour treatment. By leveraging advancements in medical technology, clinicians can potentially identify tumours at earlier stages, opening doors for more effective treatment options and ultimately, improved patient outcomes. This research explores the potential of image processing and deep learning techniques to develop a more accurate and automated system for liver tumour detection in medical images [5, 6]. Such a system could significantly contribute to earlier diagnoses and improved prognoses for patients with liver cancer.

2 Literature Survey

When computer programs aid in diagnosing liver tumours, identifying, and outlining the tumour (detection and segmentation) are crucial steps performed before treatment. Our research introduces a new method based on a phase attention mask R-CNN architecture. This method can simultaneously detect and segment liver tumours in CT scans that use multiple phases. The attention mechanism within the network selectively focuses on important features from each phase of the scan at various image resolutions [7]. Cancer is a widespread health concern. This study explores the potential of quantitative biomarkers extracted from routine CT scans to develop a reliable clinical tool for diagnosing hepatocellular carcinoma (HCC). Current clinical methods can be time-consuming and resource intensive. To address this challenge, this research proposes a deep learning approach called Successive Encoder-Decoder (SED). This approach aims to assist in the automated segmentation of liver lesions and tumours within CT images, potentially improving the efficiency and accuracy of clinical diagnosis and treatment planning [8, 9].

Medical imaging plays a vital role in supporting diagnosis, and treatment decisions. It also provides valuable information to surgeons for planning surgeries and managing patients during the perioperative period (around the time of surgery). While semi-automatic methods for segmenting organs and tumours have been explored extensively, recent advancements in deep learning (DL) algorithms have sparked increased interest in automated organ segmentation. This study aims to discover the most effective deep learning architectures for liver segmentation by adapting and comparing cutting-edge deep learning frameworks utilized across diverse domains [10, 11].

Cancer, a prevalent illness, has seen a rise in mortality rates in recent times. Among both men and women, lung cancer stands out as the most frequently diagnosed form. It occurs due to uncontrolled cell growth within the lungs. These cells fall into two categories: benign and malignant. Benign tumours are generally harmless, remaining localized and possessing a regular, smooth shape. In contrast, malignant tumours are aggressive, capable of spreading to other areas of the body, forming new cancerous growths with irregular shapes [12].

Maintaining optimal liver health is crucial for overall well-being, given its vital role in the body. However, many individuals neglect their health, leading to a prevalence of liver issues globally due to poor lifestyle choices. This study aims to detect liver tumours using classification techniques. Abdominal CT scan images were analysed, and

a machine learning algorithm-based classification technique was employed to distinguish liver tumours. Features were extracted using the GLCM method, and the study suggests employing the random forest approach for image classification [13].

Machine learning and deep learning algorithms are increasingly prominent in medical imaging research [14]. Significant efforts are underway to enhance medical imaging applications, particularly in diagnosing errors in disease diagnostic systems that could lead to unclear medical treatments. These algorithms play a crucial role in predicting early disease symptoms through medical imaging. Specifically, convolutional neural networks have emerged as a specialized methodology for analysing medical images [15].

Precisely delineating the ischemic lesion in unimodal magnetic resonance imaging (MRI) poses challenges due to subtle intensity variations between the lesion and healthy tissues. Consequently, multispectral MRI techniques are employed to enhance the understanding of brain tissue properties. Traditional lesion detection methods depend on extracting specific manually crafted features to differentiate normal and abnormal brain tissues. However, identifying these distinguishing features is complex, as their effectiveness varies across different MRI modalities. Convolutional neural networks (CNNs) offer a solution by automatically extracting features [16]. They can effectively learn global features from images, facilitating image classification [17].

3 Methodology

The deep learning network framework for our proposed method follows a sequence comprising pre-processing, feature extraction, segmentation, and classification. The overall structure of our approach for liver tumour detection is illustrated in Fig. 1.

The proposed methodology for liver tumour detection in computed tomography (CT) images utilises a convolutional neural network (CNN) and encompasses several stages. Initially, CT images undergo preprocessing, including standardization through resizing, contrast enhancement via histogram equalization, and noise reduction using a bilateral filter. Subsequently, K-Means Image Based Segmentation is applied to delineate liver regions for focused analysis. Central to the approach is the utilization of a CNN, renowned for its ability to discern hierarchical features, facilitating precise tumour identification. By leveraging deep learning, particularly CNNs, the methodology aims to augment the accuracy and reliability of liver tumour detection in CT scans.

3.1 Image Pre-processing

Image pre-processing plays a crucial role in liver tumour detection for several reasons. Initially, it helps standardize the input images, ensuring uniformity in size and format, which is essential for subsequent analysis steps. Secondly, pre-processing techniques such as histogram equalization and bilateral filtering are employed to enhance the quality of images by improving contrast and reducing noise respectively. The input image of CT liver tumour has been taken from the datasets. The input image is resized to a standardized dimensions to ensure consistency in the following phases which is shown in Fig. 2.

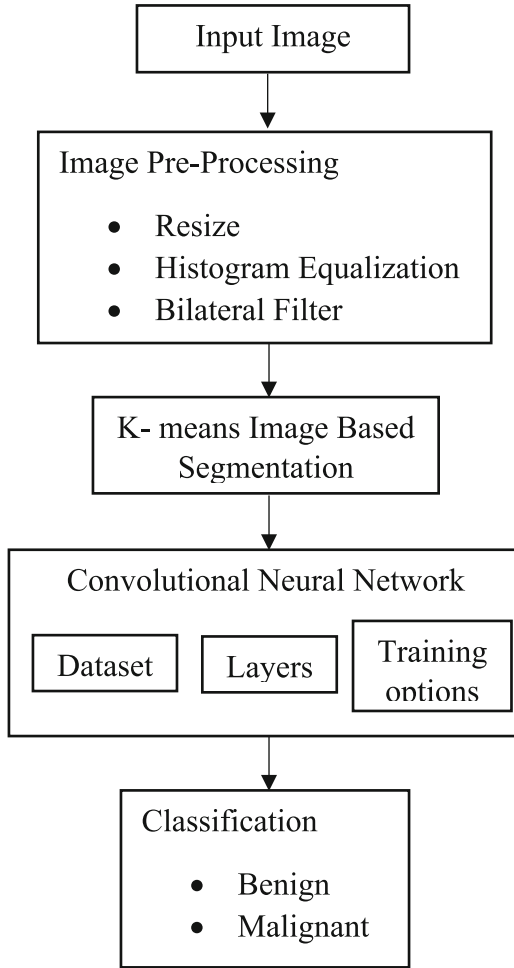


Fig. 1. Block diagram of proposed approach.

Histogram Equalization. Is particularly useful in liver tumour detection as it redistributes pixel intensity values, thereby enhancing the contrast of the image. This enhancement aids in making subtle differences in pixel intensities more apparent, which is vital for distinguishing between healthy liver tissue and tumour regions, the difference between input image and histogram equalized image can be observed in Fig. 3. The histogram equalization is calculated as follows:

$$G(i, j) = \text{round}\left(\frac{C}{MN} \sum_{k=0}^{f(i,j)} n_k\right) \quad (1)$$

where:

- $G(i, j)$ is the intensity value of the pixel at position (i, j) in the equalized image.



Fig. 2. Input Image.

- C is the maximum pixel intensity value (typically 255 for 8-bit images).
- M and N indicates the image dimensions.
- $f(i, j)$ is the intensity value of the pixel at position (i, j) in the original image.
- n_k is the cumulative histogram up to intensity level k .

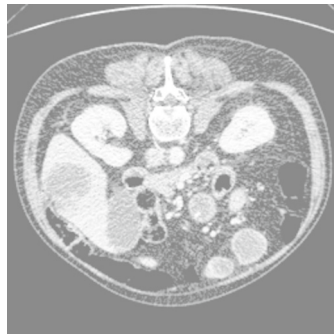


Fig. 3. Histogram equalized image.

Bilateral Filtering. Is utilized to reduce noise while preserving the edges and important features within the image. In liver tumour detection, where the identification of precise boundaries is crucial, bilateral filtering helps in smoothing out noise without significantly blurring the edges of the tumour or surrounding tissues which can be seen in the Fig. 4. This ensures that the subsequent analysis steps, such as segmentation and feature extraction, are performed on clean and clear images, leading to more accurate results in tumour classification. The bilateral filtering is calculated as follows:

$$I_D(i, j) = \frac{\sum_{k,l} I(k, l) \omega(i, j, k, l)}{\sum_{k,l} \omega(i, j, k, l)} \quad (2)$$

where:

- I_D is the denoised intensity of pixel (i, j) .
- $I(k, l)$ is the intensity of pixel (k, l) .
- $\omega(i, j, k, l)$ is the weight based on spatial and intensity differences between pixels (k, l) and (i, j) .

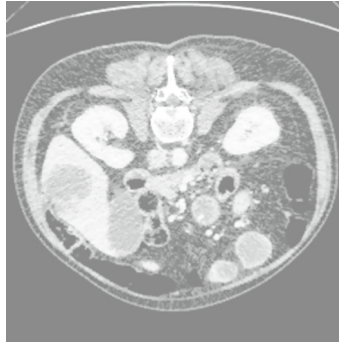


Fig. 4. Bilateral filtered image which smoothens the histogram equalized image by reducing the noise.

3.2 K Means Clustering Based Image Segmentation

K means image segmentation plays an important role in image analysis tasks such as early tumour detection. This algorithm divides an image into unique, non-overlapping clusters based on similarities in pixel intensities. In the context of image segmentation, each pixel's intensity values are treated as features, and K-means clustering assigns each pixel to one of the K clusters based on its similarity to the cluster centroids. Therefore, k-means clustering process is most suitable method for feature extraction [18]. In liver tumour detection, K-means clustering can be used to segment the CT images into different regions, such as liver tissue, tumour regions, and background as shown in Fig. 5. This segmentation helps in isolating the tumour regions for further analysis. This analysis aids in identifying the regions of interest and shows the effectiveness of the segmentation process in highlighting image features.

3.3 Convolutional Neural Network

Convolutional neural networks (CNNs) have become potent instruments for tasks involving image analysis, including liver tumour detection. In this section, we discuss the application of CNNs in liver tumour detection, covering datasets used, layers, and training options.

Datasets. The effectiveness of CNNs in liver tumour detection relies on the availability of diverse and well-curated datasets for training and validation. Figure 6 shows the sample datasets of benign and malignant liver tumours used for training the CNN model.

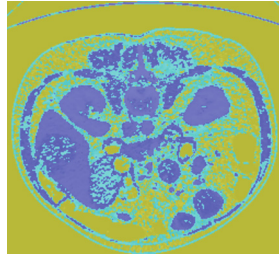


Fig. 5. Labelled RGB image after K- means clustering based image segmentation.

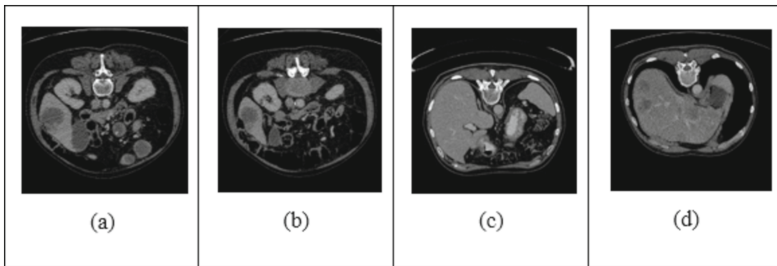


Fig. 6. Sample CT images containing liver tumours from the datasets.

Layers. The network architecture for liver tumour detection relies on a series of key layers designed to extract meaningful features and facilitate accurate classification. Each layer contributes uniquely to the overall performance of the Convolutional Neural Network (CNN) [19], ensuring robustness and efficiency in detecting tumours.

Batch Normalization Layer. This layer enhances training stability and convergence speed by normalizing activations across mini batches. This normalization reduces sensitivity to initialization and facilitates the use of higher learning rates, expediting training while improving generalization.

ReLU Layer. Employed after batch normalization layers, Rectified Linear Unit (ReLU) layers introduce non-linearity crucial for capturing complex patterns within the data. By setting negative values to zero, ReLU layers enhance feature representation, fostering the network's ability to learn discriminative features. A ReLU layer executes a threshold operation on each element, setting any input value below zero to zero. This is denoted by the ReLU representation as follows:

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (3)$$

Cross Channel Normalization Layer. This layer fosters robust feature learning by performing channel-wise local response normalization, enhancing the network's ability to discern patterns across different channels. Through normalization based on neighbouring channels, this layer promotes feature consistency and improves model generalization.

Max and Average Pooling Layer. Essential for down-sampling feature maps and controlling model complexity, these layers extract dominant features while preserving spatial information. By reducing spatial dimensions, Max and Average Pooling layers facilitate translation invariance and computational efficiency, crucial for effective tumour detection.

Fully Connected Layer. The final stage in feature aggregation and classification, Fully Connected layers integrate extracted features from preceding layers to make accurate predictions. In liver tumour detection, these layers amalgamate local information to identify larger patterns indicative of tumour presence, enabling precise classification.

Training Options. The dataset images have been utilized to train a CNN model for liver tumour detection, enabling precise classification of liver scan images. This trained model enhances diagnostic capabilities by accurately identifying liver tumours. The training process has been shown in Fig. 7.

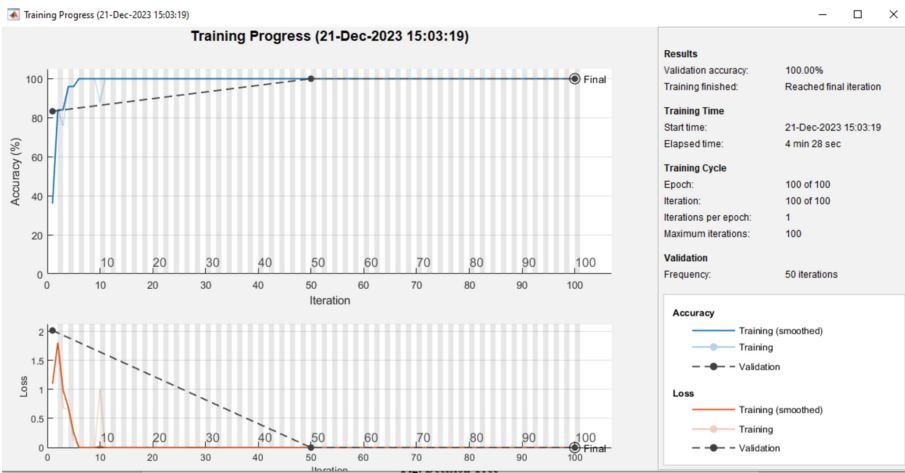


Fig. 7. Training process of the CNN model.


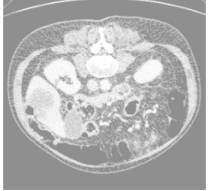


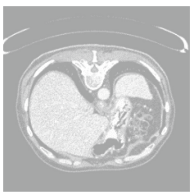

3.4 Classification

The datasets have been classified into two types which are either benign liver tumours or malignant liver tumours based on CNN training model (see Table 2(b)).

4 Results and Discussions

The proposed methodology has been structured into multiple phases. Initially, an input image has been taken from the datasets and it is resized to standardized dimensions (see Table 1(a)). Histogram equalization is utilized on the resized input images to improve the overall contrast. (See Table 1(b)). After the histogram equalization, bilateral filter is applied to preserve edges and for noise removal (see Table 1(c)).

Table 1. Image pre-processing steps.

S. No.	(a) Input Image	(b) Histogram Equalized Image	(c) Bilateral Filtered Image
1			
2			

After image pre-processing, the bilateral filtered images are converted to labelled RGB images by using K-means clustering based image segmentation (see Table 2(a)). Using Convolutional Neural Network, the deep learning methodology automatically compares the labelled RGB images with trained datasets and classify them as benign or malignant liver tumours. The classification of liver tumours in CT images are shown in Table 2(b).

4.1 Performance Metrics

CT scans were utilized for patient examination, with diagnostic outcomes assessed using parameters true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Metric values like accuracy, sensitivity, specificity, and precision are determined based on these parameters, as represented by the expressions (4), (5), (6), and (7) below.

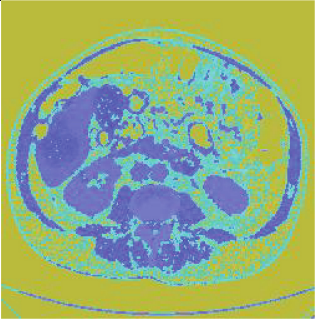
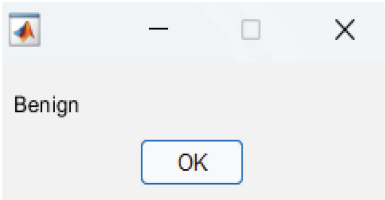
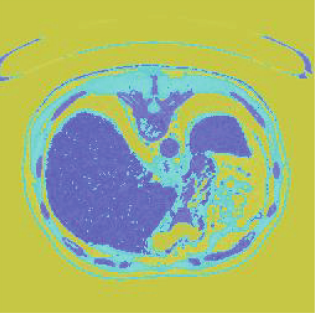
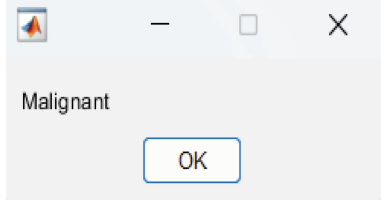
Accuracy. Indicates the proportion of correctly identified cases (both benign and malignant tumours) among all cases examined and calculated using (4)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Sensitivity. Defined by (5) measures the proportion of actual tumours (both benign and malignant) correctly identified by the system.

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

Table 2. Classification of liver tumours in CT images.

S. No.	(a) K- means Segmented Image	(b) Classified Image
1		
2		

Specificity. Defined by (6) indicates the proportion of non-tumour regions (healthy liver tissue) correctly identified by the system as negative.

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

Precision. Defined by (7) measures the accuracy of positive predictions made by the system, particularly in distinguishing between benign and malignant tumours.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

The overall metric values such as accuracy, sensitivity, specificity, and precision of two different approaches namely Random Forest (RF), and Convolutional Neural Network (CNN) are represented in Fig. 8. This comparison graph demonstrates our proposed method had better metric values when compared to existing method. A significant change can be seen in overall accuracy increasing from the range 92.3% to 98.7% when used proposed method compared to existing method. Furthermore, other metric values have also shown better performance. It is worthy to mention here that detection of liver cancer using image processing and DL has a great potential for future internet of things (IoT)-enabled smart city applications [20–22].

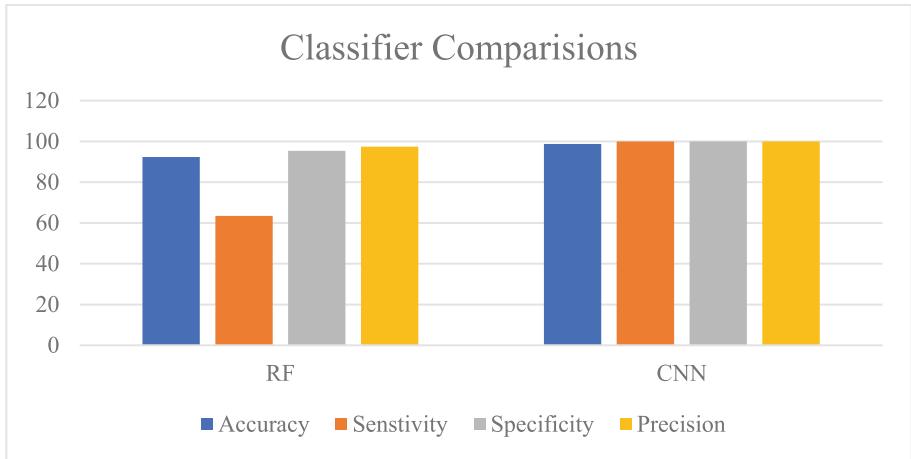


Fig. 8. Measures of Accuracy, Sensitivity, Specificity, and Precision for comparison.

5 Conclusion

In conclusion, the deep learning approach utilising convolutional neural network (CNN) marks a remarkable advancement in liver tumour detection from CT scans. The meticulous pre-processing steps, involving image resizing, histogram equalization, and noise reduction with bilateral filtering, ensure high-quality input data. Additionally, K-means image-based segmentation refines the identification of the liver region. Notably, CNN leverage the power of deep learning to achieve exceptional tumour detection accuracy, paving the way for improved diagnoses. This synergy between advanced image processing and deep learning holds immense potential for the future of medical diagnostics, particularly by boosting the efficiency and precision of liver tumour detection in CT scans.

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