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RESEARCH ARTICLE

CLASSIFICATION OF LIVER CANCER VIA DEEP LEARNING BASED DILATED ATTENTION CONVOLUTIONAL NEURAL NETWORK

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Abstract – Liver cancer occur when normal cells develop aberrant DNA alterations and reproduce uncontrollably. Patients with cirrhosis, hepatitis B or C, or both have an increased risk of developing the progressing stage of cancer. The radiologists spend more time for detecting the liver cancer when analysing with traditional methods. Early detection of liver cancer can help doctors and radiation therapists identify the tumours. However, manual identification of liver cancer is time-intensive and challenging process in the current scenario. In this work, an automated deep learning network is designed to classify the liver cancer in its initial phase. At first, the CT scans are gathered from the publicly available LiTS database and these gathered images are pre-processed using Gaussian filter is used for reducing the noises and to smoothen the edges. The liver region is segmented using Enhanced otsu (EM) method is utilized to segment the liver region separately from the pre-processed input images. Afterwards, Dilated Convolutional Neural Network (DCNN) with the attention block is employed for classifying the liver cancer into tri-classes such as normal controls (NC), hepatocellular carcinoma (HCC) and cholangiocarcinoma (CC) cases based on the extracted features. The efficiency of the proposed DA-CNN is evaluated using the attributes viz., accuracy, sensitivity, precision, specificity, and F1-score values are computed as classification results. The experimental fallouts disclose that the DA-CNN attains an accuracy range of 98.20%. Moreover, the proposed DA-CNN advances the overall accuracy by 3.25%, 5.29%, and 0.99% better than Optimised GAN, OPBS-SSHC, HFCNN respectively.

Keywords *– Liver cancer, Deep learning, CT images, Attention block, Enhanced otsu method.*

1. INTRODUCTION

Liver cancer (LC) is a malicious tumour that originates in the liver cells, medically referred to as hepatocellular carcinoma (HCC). Globally, LC is the prevalent and aggressive forms of cancer with a high mortality rate [1]. LC can be caused by chronic liver diseases like hepatitis B or C infection, cirrhosis, heavy liquor consumption, exposure to aflatoxins, and certain genetic conditions [2, 3]. In most cases, LC progresses silently, with symptoms frequently appearing only after the condition has progressed. In addition to fatigue, jaundice, and unexplained weight loss, stomach pain is another symptom. LC poses significant challenges due to its insidious onset, complex etiology, and limited treatment options, resulting in a high mortality rate [4, 5].

Regular screenings and timely medical intervention are essential for early detection, which improves prognosis and increases the efficacy of existing treatment modalities. Diagnostic procedures often include imaging studies, blood testing, and occasionally a liver biopsy [6, 7]. Depending on the cancer's stage, a patient may receive chemotherapy, radiation therapy, targeted therapy, surgery, or a liver transplant among other treatments [8]. The prognosis for liver cancer is still poor despite improvements in treatment options, underscoring the vital significance of early intervention, routine screening, and preventative measures. The precision and efficiency of traditional diagnostic procedures such as MRI, CT and US imaging techniques are limited which frequently results in incorrect or delayed diagnosis [9, 10].

Machine learning (ML) [11] and Deep learning (DL) [12] has emerged as a promising tool in medical imaging analysis, including the identification and diagnosis of LC. DL algorithms [13] can effectively learn intricate patterns and features from vast amounts of medical imaging data, enabling them to detect subtle abnormalities indicative of liver cancer with high accuracy and efficiency [14]. In this research, we explore the application of DL technique for the detection of liver cancer using CT scans. The primary contributions of the work are summarised as:

- Initially, the CT images are gathered and pre-processed using Gaussian filter is used for reducing the noises and to smoothen the edges.
- An Enhanced otsu (EM) method is used to segment the liver region separately from the pre-processed CT images.
- Afterwards, Dilated Convolutional Neural Network (DCNN) induced with attention block is employed for classifying the liver cancer into normal controls (NC), hepatocellular carcinoma (HCC) and cholangiocarcinoma (CC) cases.
- The efficiency of the proposed DA-CNN is evaluated using the attributes viz., accuracy, sensitivity, precision, specificity, and F1 score for computing the classification results.

The rest of the paper was scheduled as follows in advance. A summary of the literature was provided in Section 2, followed by an extensive description of the proposed DA-CNN methodology for LC classification in Section 3, results and discussion in Section 4, and Section 5 holds the conclusion part.

2. LITERATURE REVIEW

In this section, the challenges associated with traditional diagnostic methods was discussed and spotted the use of DL-based approaches in overcoming these challenges. Furthermore, the recent advancements and existing architectures in DL was reviewed for LC recognition, emphasizing their strengths and limitations in this section.

In 2022, Amin et al., devised [15] an optimized GAN for image synthesis, followed by localization using an improved model. Deep features from pre-tuned ResNet50 were inputted to the YOLO-v3 model. Segmentation employs a pre-trained InceptionResNetV2 model for Deeplabv3, fine-tuned with annotated masks. Experimental findings demonstrate a testing accuracy exceeding 95%.

In 2021 Kushnure, and Talbar putforward [16] a multi-scale approach that augmented the CNN's receptive field by incorporating multi-scale features, thereby capturing both local and global characteristics at a better granularity. Experimental results demonstrated improved efficiency of the system on the 3Dircadb database. Specifically, the method attained a dice score of 97.1% and 84.1% for LC detection.

In 2021 V. Hemalatha et al., [17] introduced a method that combines Region of Interest (ROI) extraction with the Adaptive WS technique for the detection of LC. This methodology incorporates ANN techniques for denoising, scanning, extraction, and segmentation. To recognize LC within real-time datasets, a feed-forward neural network was employed. Subsequently, the extraction of features was conducted using GLCM techniques.

In 2020 B. Sakthisaravanan et al. [18] designed an OPBS-SSHC approach for liver tumor identification, integrating segmentation and similarity-based hybrid classification. Noise removal during preprocessing was followed by edge enhancement using a frequency-centered sharpening technique. Subsequently, the SSHC model classified extracted features, achieving a superior accuracy of 93% compared to other systems.

In 2020 Dong, et al., designed [19] developed a Hybridized Fully CNN for the segmentation of LC. The suggested method combines residual and pre-trained weights with the effectively extracted features from Inception. This DL system illustrates the idea of illuminating certain decision-making steps in a deep neural network was trained extensively. From the analysis the suggested HFCNN attains the accuracy of 97.22% for 50 epochs.

In 2019 Hamm., et al., [20] devised custom convolutional neural network (CNN) through iterative refinement of the network architecture and training samples. The final CNN comprised three convolution layers with Relu, two max pooling layers, and two fully connected layers. Monte-Carlo cross-validation was employed during this method development process. Upon completion of model engineering, the classification accuracy of the finalized CNN reached 92.0%.

According to the literature review, the existence of noise abnormalities in CT scans poses challenges for liver segmentation. Given the intricate structure of the liver, many clinical decisions support schemes, particularly those employing ML techniques, rely heavily on segmentation. Utilizing CT scan images for automated LC diagnosis is pivotal due to potential variations in structural alterations among patients. To address these issues, a novel DA-CNN model utilizing CT images for early-stage LC identification has been proposed. This study introduces a region-based segmentation technique for recognizing the LC area, ultimately aiming to design an efficient approach for LC categorization.

3. PROPOSED METHOD

This proposed section presents a novel deep learning-DA-CNN model to identify the LC cases from the available LiTS dataset. The overall workflow of the proposed LC identification method is displayed in Figure 1.

3.1. Dataset description

This study utilizes the common LiTS dataset from [21] which comprising 194 CT scans containing lesions and 201 liver CT images. The diverse and varied characteristics of tumor lesions pose significant challenges for automated segmentation. The objective is to devise segmentation techniques capable of automatically detecting liver tumours in contrast-enhanced CT scans. The test dataset comprises 70 CT scans, while the training dataset consists of 130 CT scans. This task is coordinated with MICCAI 2017 and ISBI 2017.

3.2. Gaussian filter

Pre-processing of medical images is essential for improving the quality and interpretability of diagnostic results. The Gaussian filter is a linear filter which reduces noise and smooths images while maintaining important features. In the image, each pixel is subjected to a weighted average determined by a Gaussian function. A Gaussian function smoothes the image by giving more weight to pixels near the center of the filter window.

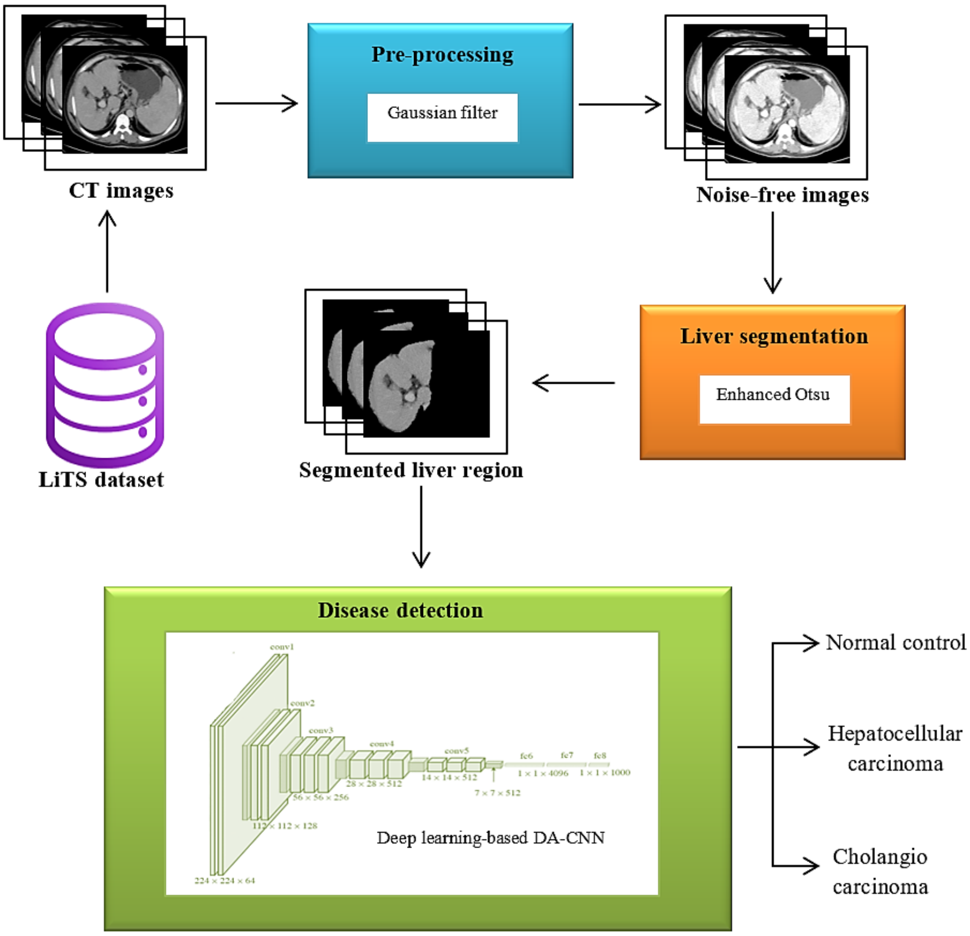

Figure 1. The outline of the overall proposed LC identification model

This gaussian function is mathematically determined as,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where $G(x,y)$ represents the Gaussian kernel, σ is the standard deviation of the Gaussian distribution, which controls the amount of smoothing applied to the image, x and y are the spatial co-ordinates of the filter. In the next step, the input is convolved by a Gaussian filter to create the smoothed output. Based on the specific requirements, the kernel size and σ value was changed in the properties of the input images.

3.3. Enhanced otsu method

After filtering the image is subjected to a segmentation process, where the Enhanced otsu (EM) method is used for liver region segmentation. In this EM method, the discriminate analysis is used where the threshold value is set in retaining the pixels of the image when it is split into two such classes. C_1 and C_2, where $C_1 = \{0,1,2,\dots t\}$ and $C2 = \{t+1, t+2, \dots M-1)$.The values corresponding to the class variance (within and in between) and the total variance are analysed in such a manner that to determine very effectively. Here n_i is considered as the no.of pixels along with grey level (n) and (i), which is considered as the total no.of pixels in the image and is represented as

$$\Gamma = \sum_{\tau=0}^{M-1} \Gamma_i + \sum_{\sigma=1}^{N} T(n-1) \quad (2)$$

As per the condition, Pi is represented as the possibility of incidence of the modified grey level i. Otsu method used here will analyse the becoming aspects of the threshold values in order to analyse the obtained optimal values for the given image. The threshold value t of the given image will indicate the $C_1 = \{0,1,2,\dots t\} and C2 = \{t+1, t+2, \dots M-1)$. This is mathematically expressed as

$$\Gamma_{rs}(x) = \sum_{x=1}^{\infty} x(k). \frac{1}{\vartheta\sqrt{\sigma_x}}. \, exp\left[\frac{P_k}{2\sigma_x}\right] \quad (3)$$

The maximum value of the segmented image is used for evaluating the classes C1 and C2 in a separate process. This could be possible by fixing the original image to a certain extent in combination with the histogram equalization methods. The Corresponding equation representing the output value of segmentation is given as

$$X_G[P]_\alpha = \sum_{x,y\in\gamma} \Gamma_{rs}(x-y) + \frac{1}{R_p} \sum_{x.y} [P_x - P_y] \quad (4)$$

Here the lower bound is gathered by the possibility of considering the original image with a single grey Constraints from the lower bound and the upper bound in correlation with the images which is of different values.

3.4. Dilated Attention-Convolutional Neural Network

In DA-CNN, an attention block is integrated with DCNN for focusing the most relevant features while extracting for better classification results. DCNN introduce dilated convolutions, also known as atrous convolutions, which enable capturing larger receptive fields without increasing the number of parameters. Dilated convolutions enable a larger responsive region without adding more parameters. In liver CT images, DCNN excel at extracting these features by effectively capturing spatial relationships at different scales. By employing dilated convolutions with increasing dilation rates across multiple layers, the network can aggregate information from a wide range of spatial contexts, enabling it to discern subtle patterns indicative of liver lesions. In particular, the convolution process can be expressed as follows assuming input features X and a filter K as follows

$$(X_P * F_K)(l,k) = \sum_n \sum_m X_P\,(l - n * d_r\,, k - m * d_r) F_K(n,m) \quad (5)$$

Where, d_r be the dilated rate and F_{K1} filter captures larger patterns because it encompasses a broader range of features than the F_{K2} filter, which operates as a standard convolutional filter and is ideal for extracting few patterns.

$$U = n + (n-1) \times (D_i - 1) \quad (6)$$

The image integrating matrix U is continually scanned by the convolution kernel. Dilated convolutions increase the interval of scanning features and add a few areas among convolution kernels. The height of the equivalent convolution kernel, essentially determines the number of images expressed as U in equations (6), assuming that the dilation rate is Di.

$$c_n = X(W' \times s^k_{i:i+u-1} + d) \quad (7)$$

The feature c_n is retrieved and expressed as follows after the convolution procedure.

$$Q_i = K_m = V_m = o_p \quad (8)$$

The outcomes of the dilated convolution o_p are the beginning values for the query matrix Qi, key matrix K_m, and value matrix V_m, as illustrated in the above equation. The attention block includes improved focus on relevant spatial information, enhanced feature learning, and the ability to adaptively attend to different parts of the input data for better task performance. To learn a spatial weight map W_m and then multiply it by the associated spatial locations.

$$W_m(C) = sigmoid\left(c^k([Avgpool(C); Maxpool\ (C)])\right) \quad (9)$$

where c^k represents a convolution operation with kernel size k. This module produces a spatial attention-map by considering the importance of each spatial location within the feature maps. The spatial-attention mechanism is illustrated as,

$$M_s(f) = \sigma(f\left(f_j(f_{avg} + f_{max})\right)) \quad (10)$$

where f_j is the join operation, f_{avg} indicates global average pooling and f_{max} global max pooling features respectively. In order to calculate attention weights, self-attention mechanisms use relationships between multiple variables in the same input sequence. As a result, DCNN is particularly helpful for tasks following feature extraction, as it can efficiently collect long-range dependencies and contextual information. To minimize spatial dimensions and reduce the sample size of feature maps, the DA-CNN can additionally include pooling layers. After feature extraction, the dilated CNN can be utilized for classification tasks such as distinguishing between benign and malignant lesions or identifying specific types of liver abnormalities. The extracted features serve as rich representations of the input images, which was the input to fully connected layers for tri-LC classification.

4. RESULTS AND DISCUSSION

This section uses Matlab-2020b to implemented the experimental fallouts and assess the efficacy of the proposed DA-CNN. The CT images as input are gathered from the accessible LiTS dataset. The comparison provides a detailed description and analysis of the total accuracy rate besides the efficiency of the proposed DA-CNN is also provided in this section.

4.1. *Efficacy scrutiny*

The effectiveness of the proposed DA-CNN was calculated using the network parameters viz., precision (P), recall (R), F1 score (F1), accuracy (A), and specificity (S).

$$A = \frac{(TP+FP)}{(TP+TN+FN+FP)} \quad (11)$$

$$P = \frac{TP}{TP+FP} \quad (12)$$

$$S = \frac{TN}{TN+FP} \quad (13)$$

$$R = \frac{TP}{TP+FN} \quad (14)$$

$$F1 = 2\left(\frac{P*R}{P+R}\right) \quad (15)$$

where TP and TN means true positives and negatives of the images, FP and FN specifies false positives and negatives of the images. For the experimental setup, the tri classes of LC are defined as “class-0” for NC, “class-1” for HCC, and “class-2” for CC respectively. The competence of the DA-CNN model for classifying several forms of LC is tabulated in Table.1 and it is visually signified in Figure 2.

Table 1. Efficacy evaluation of our DCNN model

Classes	A	S	P	R	F1
class-0	98.62	97.18	97.21	97.14	97.62
class-1	97.44	96.23	96.18	97.32	97.25
class-2	98.55	97.02	97.22	98.08	98.43

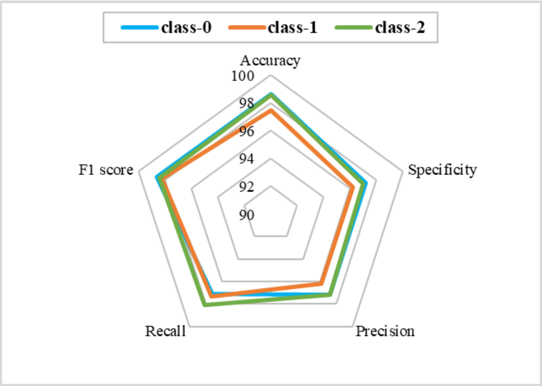

Figure 2. Classification performance analysis for tri-LC classes

The proposed DA-CNN model classified the three different LC classes from the CT images as shown in Figure 3 The proposed DA-CNN is assessed in term recall, accuracy, precision, specificity, and F1-score. The proposed DA-CNN achieves an overall accuracy of 98.20%. Also, the proposed DA-CNN exhibits an overall S of 96.81%, P of 96.87%, R of 97.51%, and an F1 of 97.76% respectively.

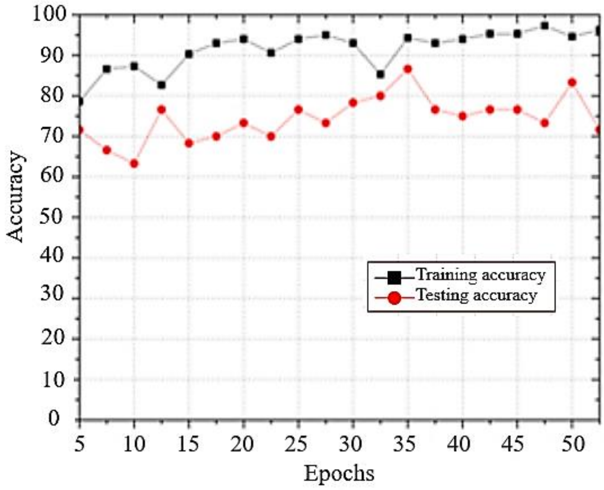

Figure 3. Accuracy graph of the proposed DA-CNN

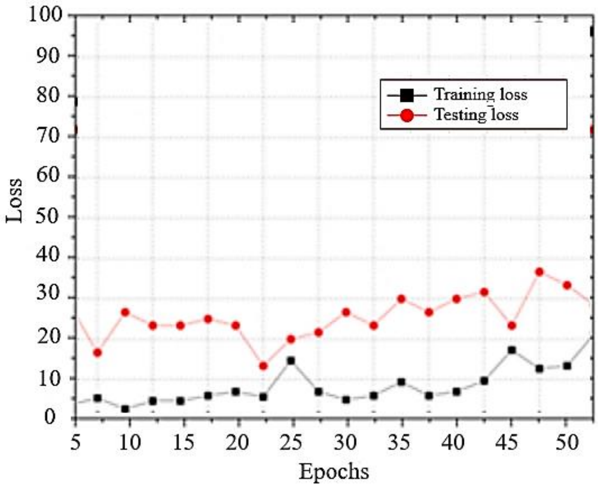

Figure 4. Loss graph of the proposed DA-CNN

Figure 3 depicts the accuracy curve, shows the accuracy range on the vertical axis against the number of epochs on the horizontal axis. When the no. of epochs raises, the proposed DA-CNN demonstrates an improvement in accuracy. Figure 4 shows the epochs and loss, illustrating that the DA-CNN experiences a reduction in loss with an increase in epochs. The proposed DA-CNN model proven effective in accurately classifying the tri-LC cases from the gathered CT images. According to the findings, the DA-CNN achieves significant performance in classification accuracy of 98.20%.

4.2. Comparative analysis

In this analysis, the competence of proposed and existing models was estimated using different metrics. The comparison assessment was competed among the proposed D-CNN with different classification techniques. The comparison of traditional classification networks is illustrated in Table.2.

Table 2. Comparison of traditional models for classification

Models	Precision	Recall	F1 score	Specificity	Accuracy
ANN [22]	87.3	84.5	87.6	85.4	84.5
SNN [23]	88.5	87.2	86.4	90.2	92.5
DACNN	96.8	97.5	97.7	96.8	98.4

Table 2 presents a comparison of various conventional DL networks, identifying the best classification accuracy achieved. Though, despite their utilization, classic DL networks didn't yield superior outcomes in comparison to the proposed DCNN. The proposed DCNN increases the overall accuracy by 11.0%, and 9.87% better than ANN and SNN respectively.

Table 3. Accuracy assessment among Proposed and Existing models

Authors	Methods	Accuracy
Amin., et al., [15]	Optimized GAN	95.0%
Sakthisaravanan, B. and Meenakshi [18]	OPBS-SSHC	93.0%
Dong., et al., [19]	HFCNN	97.22%.
Proposed model	DA-CNN	98. 42%

Table 3 illustrates the assessment of the DA-CNN model with prior models based on LiTS dataset. The proposed DA-CNN model advances the overall accuracy by 3.25%, 5.29%, and 0.99% better than Optimized GAN [15], OPBS-SSHC [18], HFCNN [19] respectively. Though, the existing networks not performed well when compared to the proposed network. So, the estimated fallouts of the proposed DA-CNN are extremely consistent for classifying the liver cancer in its early stages based on CT images from LiTS datasets.

5. CONCLUSION

This paper presents an automated deep learning DA-CNN for the identification of LC in its primary phases. The images are gathered from the publicly available LiTS database and these gathered images are pre-processed using Gaussian filter is used for reducing the noises and to smoothen the edges. The EM technique was used for segmenting the liver region separately from the pre-processed CT images. Afterwards, DA-CNN was employed for identifying the LC into tri-classes. The efficiency of the proposed DA-CNN is evaluated using the attributes like accuracy, sensitivity, precision, F1 score, and specificity values. The experimental fallouts disclose that the proposed DA-CNN attains an accuracy of 98.45%, that was comparatively better than the prior techniques. The proposed DCNN increases the overall accuracy by 11.0%, and 9.87% better than ANN and CNN respectively. Moreover, the proposed DA-CNN model advances the overall accuracy by 3.25%, 5.29%, and 0.99% better than Optimised GAN, OPBS-SSHC, HFCNN respectively. Therefore, the outcomes obtained from the proposed DA-CNN are highly trustworthy for the early-stage classification of liver cancer.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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