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Hepato Web App for Classification and Segmentation of Liver Lesions in CT Scans Using EFF Net

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Abstract*: The liver is a large organ situated in the upper right section of the abdomen, located beneath the diaphragm and above the stomach. Liver cancer is a type of cancer that originates in the liver, resulting from uncontrolled cell growth. Computed tomography (CT scan or CAT scan) is a non-invasive imaging technique that integrates x-rays with computer technology. CT scans are essential for diagnosing liver cancer in patients. A cascaded model of convolutional neural networks is employed to segment the liver, while an efficient net is used to detect liver lesions from CT scans. This method achieves an outstanding accuracy of 0.998 for both liver segmentation and liver lesion detection.*

Keywords: CNN, eff net, liver segmentation, lesion segmentation

I. INTRODUCTION

Liver imaging is crucial for patients with a known or suspected history of cancer, as the liver is a common site for metastasis, particularly from tumors originating in the colon, lung, pancreas, and stomach. Additionally, patients with chronic liver disease are at increased risk of hepatocellular carcinoma. Given the prevalence of benign liver lesions, imaging strategies should emphasize both the detection and characterization of liver lesions.[1]. Convolutional networks are highly effective visual models that produce hierarchical feature representations. When trained end-to-end from pixels to pixels, these networks alone outperform previous top results in semantic segmentation.[2]. Consequently, an automated method for segmenting hepatic tumors in CT images using an optimal statistical threshold is essential. The approach first segments the liver structure through techniques like histogram transformation, multi-modal thresholding, maximum a posteriori decisions, and binary morphological filtering.[3][4]. Multi-modal positron emission tomography and computed tomography (PET-CT) scans are widely used for this purpose because they provide complementary feature information [5]. Liver cancer is the leading cause of cancer-related deaths worldwide, and early detection through computed tomography (CT) could save millions of lives each year. However, manually interpreting hundreds of CT scans is a significant workload for radiologists, highlighting the urgent need for automated, rapid, and precise CT scan analysis. However, liver segmentation and extraction from CT scans remains a challenging bottleneck for any system.. Lung cancer is the most common fatal malignancy among both men and women, and early detection and treatment can greatly enhance patient survival rates.. This paper introduces an automated computer-aided detection (CAD) system designed to identify lung nodules in CT images at an early stages.[6]. A model selection methodology for feedforward network models based on the genetic algorithms and makes a number of distinct but inter-related contributions to the model selection literature for the feed forward networks[7]. Early detection and segmentation of liver lesions is a complex task involving multiple steps to achieve accurate results. The differences between healthy and tumorous tissue are subtle, the shape and position of the liver vary between individuals, and abdominal CT scans include other organs that must be filtered out.[8].

In this paper, I aim to capitalise on the advances made in the field of deep learning and apply those principles directly to develop a fully automatic model for liver tumour detection and segmentation in abdominal CT scans. But the liver segmentation and lesion segmentation was an challenging factor.

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Detecting brain tumors is a prevalent cause of mortality in today's healthcare landscape. Current efforts primarily focus on techniques that utilize image segmentation for brain tumor detection. Classifying and segmenting tumors from brain computed tomography (CT) image data is a crucial yet time-consuming task carried out by medical professionals.[9][10]. Similar method is used for breast cancer tumor detection also[11]. This approach employs a level set-active contour model with a minimizer function for the diagnosis and segmentation of lung tumors. A kernel-based non-local neighborhood denoising function is utilized to produce noise-free images. Additionally, second-order histogram-based feature extraction is performed to classify the images into normal and abnormal categories.[12]. However, there has been limited research on liver tumor segmentation. Automatic segmentation of the femur from computed tomography volumes is essential yet challenging for computer-aided diagnosis in orthopedic surgeries.[13]. This segmentation method extracts liver structures from abdominal CT images using an artificial neural network (NN), incorporating prior information about the liver's location and area within the abdominal cross-section, along with digital image processing techniques. The NN classifies each pixel in the image into one of three categories: boundary, liver, or non-liver. A supervised training technique is employed in this approach.[14]. In this paper I aim to classify and segment the liver with various types of hepato cancers (hepatocellular carcinoma, hepatoblastoma, fibrolemallar carcinoma or bile duct cancer) and also segmentation of liver lesions by using a CNN model from an abdominal CT-scans.

II. RELATED WORK

Mubasher Hussain, et.al[15] proposed work focuses on machine learning (ML) methods, including Random Forest (RF), J48, Logistic Model Tree (LMT), and Random Tree (RT), utilizing multiple automated Regions of Interest (ROI) for multiclass liver tumor classification. The dataset includes four tumor types: Hemangioma, Cyst, Hepatocellular carcinoma, and Metastasis. The images were converted to grayscale, and contrast enhancement was achieved through histogram equalization.An artificial bee colony (ABC) optimization algorithm was utilized as a clustering technique for segmenting the liver in CT images, where ABC determines the centroids of the clusters and identifies the corresponding regions for each cluster.[16].

Yongtao Zhang, et.al[17] proposed a novel 3D multi-attention guided multi-task learning network for simultaneous gastric tumor segmentation and LN classification, which makes full use of the complementary information extracted from different dimensions, scales, and tasks.

Nalin Nanda, Prerna Kakkar, Sushama Nagpal[18]proposed a genetically enhanced cascaded network is utilised to solve the cumbersome task of tumour segmentation from contrast-enhanced abdominal CT images. An automatically extract the liver tumor from the liver region of the CT abdominal image and to characterize the liver tumor as benign or malignant using wavelet-based texture analysis and Linear Vector Quantization (LVQ) neural network[19]. Khaled Alawneh, Hiam Alquran et.al[20]proposed a computer-aided diagnosis system that utilizes computed tomography scans to classify hepatic tumors as either benign or malignant..

Amandeep Kaur, Ajay Pal Singh Chauhan, Ashwani Kumar Aggarwal[21] proposed method involves multi-organ classification of 3D CT images for patients suspected of having liver cancer using a convolutional neural network (CNN).This CNN is specifically tailored for classifying CT images associated with liver cancer.. Ahmed M. Antera.c, Aboul Ella Hassenian[22] proposed an improved segmentation approach based on watershed algorithm, Neutrosophic Sets (NS), and Fast Fuzzy C-mean Clustering Algorithm (FFCM) for CT liver tumor segmentation is proposed. To increase the contrast of the liver CT images, the intensity values are adjusted and high frequencies are removed using histogram equalization and median filter approach.

Raunak Dey, Yi Hong[23] introduced a cascaded system that combines 2D and 3D convolutional neural networks for effective hepatic lesion segmentation. The 2D network segments the liver and larger lesions on an axial slice-by-slice basis, while the 3D network targets the detection of smaller lesions that are often overlooked by 2D-only segmentation methods. Sultan Almotairi, Ghada Kareem, et.al[24] proposed a deep learning technique initially designed for semantic pixel-wise classification of road scenes has been adapted for liver CT segmentation and classification. This model, called SegNet, uses a deep convolutional encoder–decoder structure with hierarchical encoder–decoder layers. When tested on a standard liver CT dataset, the adapted architecture achieved up to 99.9% accuracy in detecting tumors during the training phase. Zhongliang Xue, Ping Li, Liang Zhang, et.al[25] proposed model enables feature interaction across multi-modal channels by sharing down-sampling blocks between two encoding branches, reducing the impact of misleading features. Additionally, a shape-constrained region-growing algorithm is employed to automatically delineate liver metastases on CT images, allowing for comparison between automated tumor measurements and those manually outlined by radiologists.[26]. A new method and algorithm have been developed for rapid segmentation of the liver and its internal lesions from CT scans. The algorithm is fully automatic, requiring no user interaction for initialization.[27]. Sara Noor Eldin, Jana Khaled Hamdy, et.al[28] introduces a deep learning approach to diagnose breast cancer using biopsy microscopy images. Various deep convolutional networks, including VGG16, AlexNet, Inception, ResNet50, ResNet101, and DenseNet169, were applied. Among these, the top three models—DenseNet169, ResNet50, and ResNet101—achieved the highest accuracy without data preprocessing, with accuracy rates of 62%, 68%, and 85%, respectively. Current computer-aided diagnosis (CAD) research for liver cancer primarily relies on traditional feature engineering methods, which suffer from issues like redundant features and high computational cost. This work proposes an innovative bio-inspired deep learning approach to enhance predictive accuracy for liver cancer.[29].The method for liver segmentation from CT images was proposed using an adaptive threshold technique combined with morphological processing by Dr. Selvathi et.al[30].In this method, Tumor extraction is accomplished by applying Fuzzy C-Means (FCM) clustering to the liver's segmented region

III. PROPOSED SYSTEM

In this section, we will discuss the methodology used in our paper. Figure 3.1 illustrates the overall pipeline of our method. The initial step includes the collection of datasets of liver CT scans images, after that the datasets could be preprocessed, liver segmentation is done using EFF net and then predicting the type of cancer and after that the the liver lesion segmentation is done by using EFF net. Further, elaboration on the techniques used in this paper is given below.

3.1 Architecture

In this paper A convolutional neural network is employed for classifying and segmenting liver tumors from abdominal CT scans. The model first extracts the liver from the CT scan and then predicts the type of liver condition, distinguishing between normal (non-cancerous) tissue, bile duct cancer, hepatocellular carcinoma, hepatoblastoma, or fibrolamellar carcinoma. Hepatocellular carcinoma, the most common liver cancer, typically affects adults with chronic liver diseases.Bile duct cancer begins in the bile ducts, which are thin tubes that connect the liver to the small intestine. Hepatoblastoma is a rare tumor that usually appears in children under three years old, while fibrolamellar carcinoma is an uncommon liver cancer typically found in adolescents and young adults under 40. This type of cancer differs from other liver cancers because it occurs in individuals with otherwise healthy livers.

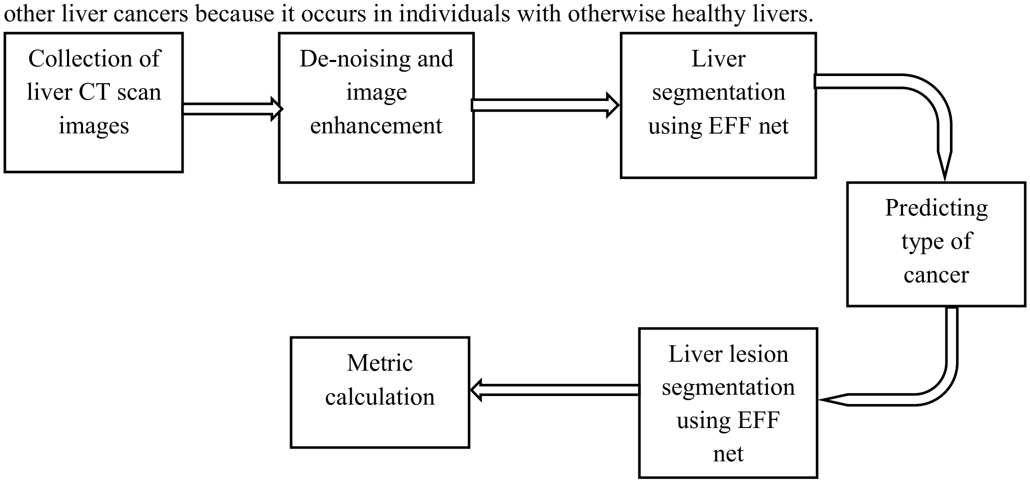

Figure 3.1 Model pipeline

The architecture includes three necessary constituents the liver segmentation, prediction of which type of cancer and the liver lesion segmentation. The architecture is illustrated in figure 3.2. The segmentation of liver basically involves retrieval of essential features from CT scan images. For liver extraction the EFF net is used. Efficient Net is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of

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depth/width/resolution using a compound coefficient. The task of segmenting lesion directly is extremely challenging due to the presence of multiple organs—often larger than the liver—in the abdominal CT scans, making extraction of hepatic tissue extremely crucial in our architecture. By using EFF net got a high accuracy.

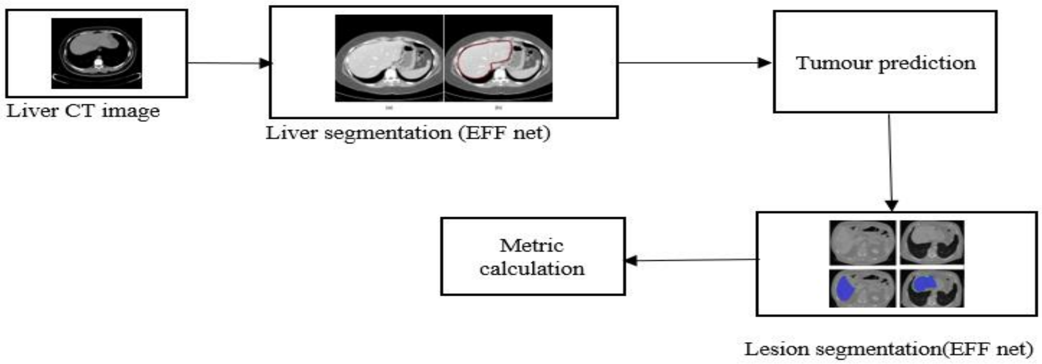

Figure 3.2 Architecture

3.2 Liver Segmentation

Due to the presence of organs other than the liver in the abdominal CT scans, the extraction of liver is critical to achieve accurate tumour segmentation. This crucial task has been achieved by the use of a convolutional neural network wherein EFF net architecture has been employed.

Convolutional Neural Network

A convolutional neural network (ConvNet) is a deep learning algorithm designed to analyze images for identification and pattern recognition. ConvNets require significantly less pre-processing compared to traditional classification algorithms. Unlike earlier methods, where filters had to be manually designed, ConvNets can learn these filters and features independently through sufficient training.

EFF net

EfficientNet focuses on architecture design and scaling. It demonstrates that with careful architectural choices, top performance can be attained with reasonable parameters. Typically, convolutional neural networks (CNNs) are developed with a fixed resource cost and subsequently scaled up to improve accuracy as more resources become available.

Before delving deeper into the architecture, it's essential to first discuss convolutional neural networks.

The layers includes batch normalization focuses on standardizing the inputs to any particular layer (i.e. activations from previous layers).Standardizing the inputs means that the inputs to any layer in the network should have a mean of approximately zero and a variance of one. Zero padding 2D layer can add rows and columns of zeros the top, bottom, left and right side of an image. There could be many other hidden layers are used for segmentation of liver and the lesions. The activation function employed here is softmax, as it is suitable for multi-class classification.Adam optimizers are used using compiling the models.

3.3 Lesion segmentation

Lesion segmentation is done only after detecting the cancerous tissues is determined. Lesion segmentation is also done by using EFF net.

IV. EXPERIMENTAL SETUP

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This section describes the datasets collected, preprocessing and various evaluation metrics used in this research.

4.1 Dataset Used

For my research I collected the datasets from Kaggle, uci.repository of about 2610 CT scan images of healthy and cancerous livers around the world

4.2 Pre-processing

The datasets could be in png format and done some enhancement and de-noising of the data sets. The CT scan images could contain organs other than liver so segmented without including organs other than liver.

4.3 Platform Used

To ease my implementation, I used python language as coding medium. Keras and Tensorflow was chosen to make our dense neural networks, and open cv library was used for preprocessing the data.

V. RESULTS

In this paper, I proposed a pipeline for segmentation of liver and its lesion using different architectures of convolutional networks along with a tumour detector. The main contributions of the paper is EFFnet used for liver segmentation and lesion segmentation which has got an highest accuracy of about 0.998. %. Figure 5.1 shows the liver cancer classification done by using EFF net. The result of prediction of liver cancer classes of my proposed model is shown in figure 5.2, So by using the proposed model a radiologist can easily classify the liver cancer and also segment the lesions if tumour could be detected.

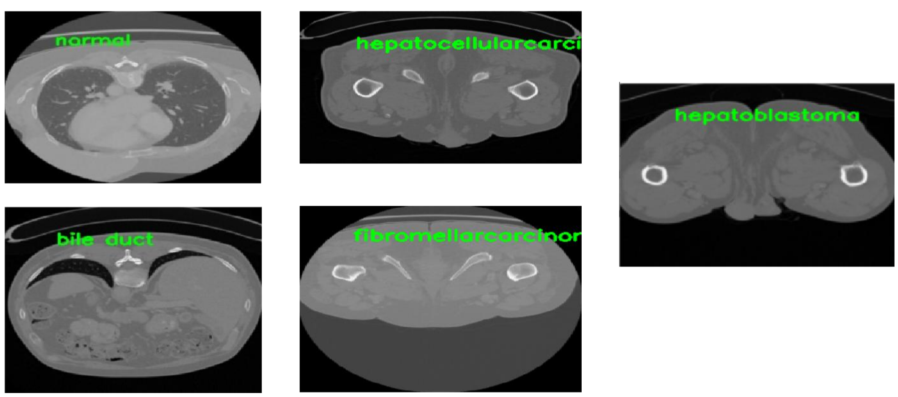

Figure 5.1 Liver cancer classification

First of all predict whether the CT scan image is a healthy (Normal) or cancerous. After that classification is done by using EFF net is shown in figure5.1 has five classes of liver cancer. The tumour region is identified by a light green colour after the classification of tumour. So once a radiologist could upload an abdominal CT scan image, the tumour could be detected and classified and then segment the

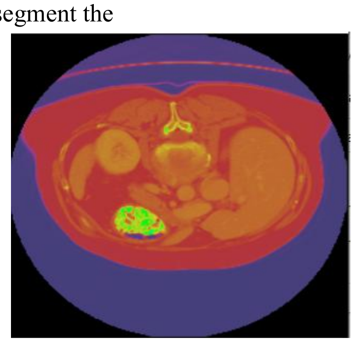

Figure 5.2 Liver cancer segmentation

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The learning curves of model accuracy is plotted in Figure 5.3 and model loss is plotted in Figure 5.4.

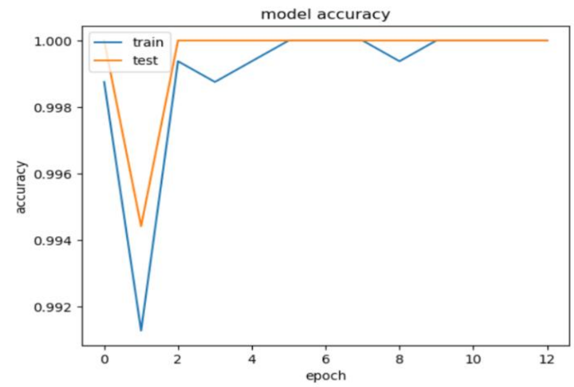

Figure 5.3 Model accuracy

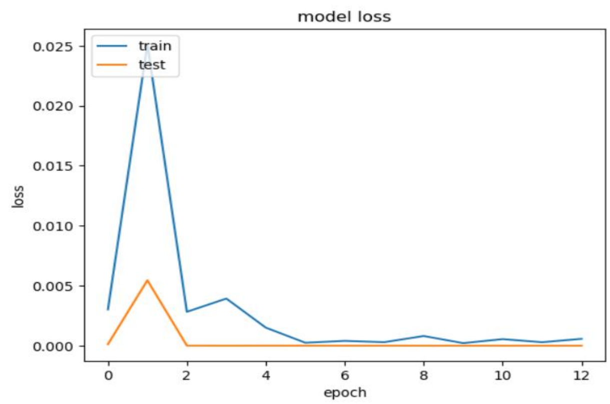

Figure 5.4 Model loss

Receiver Operating Characteristic (ROC) curves are generated and displayed to assess and compare the performance of each model. An ROC graph serves as a tool for visualizing, designing, and selecting classifiers based on their accuracy. It provides a 2D visualization of classifier performance. A commonly used metric obtained from the ROC curve is the area under the curve (AUC).Here, AUC is a share of the area of the unit square. AUC ranges between 0 and 1.0. ROC.

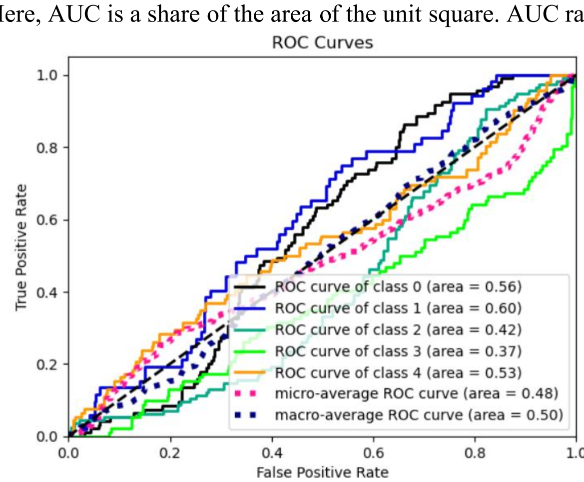

Figure 5.5 ROC curve of proposed model

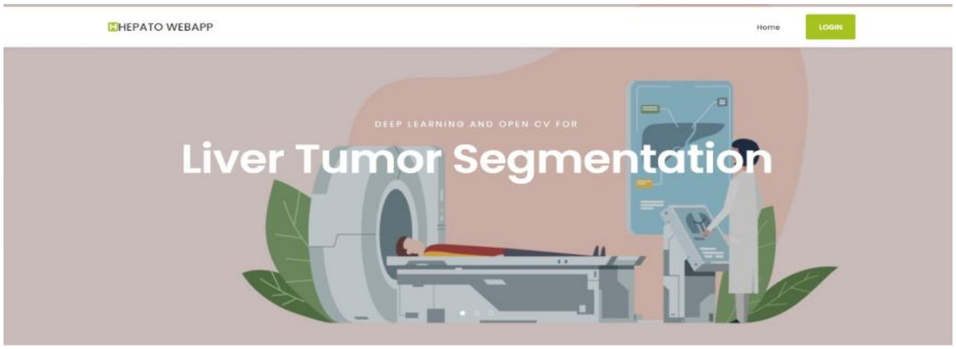

Figure 5.6 UI page

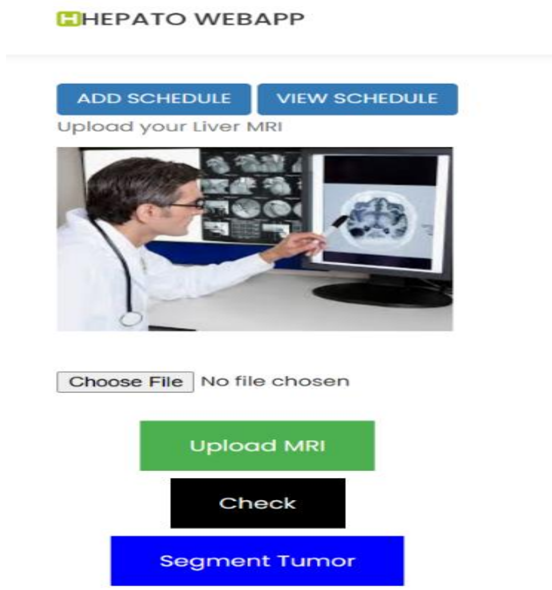

Figure 5.7 CT scan upload page

Figure 5.6 shows the user interface page. The Radiologist, Admin and Patient can login into the app by first registering with their mailId, username, password, phone number and address. Then Login into the app by using the username and password that is used at the time of registration. Figure 5.7 shows uploading page, only a radiologist can access this page. The doctor can add schedule and can view the schedule of all doctors. CT scan of liver load to this app by clicking the choose file button, then upload the CT scan and view by clicking the check button. For segmentation click on the segment tumor button.

VI. CONCLUSION AND FUTURE WORK

A pipeline for segmentation of liver and its lesion using different architectures of convolutional networks along with a tumour detection and classification of liver tumours from an abdominal CT scan images is proposed. To improve the accuracy of classification of liver cancer efficient net is used and got an average accuracy of about 99.8%. It can be concluded that in the presence of a relatively larger datasets good prediction and classification of liver cancer is obtained. Finally, the proposed method could be leveraged to serve as preliminary analysis for radiologists before preparing the final report. And this webapp can be used to schedule the appointment of radiologist and the patient can book appointment for their appropriate radiologist. Admin can either reject or confirm the appointment and admin can view the patient and radiologist details and schedule. This webapp can reduce the radiologist driven errors in liver cancer classification and lesion segmentation.

This research can be further extended by calculating the thickness and volume of cancer and classify the other type of liver cancer also.

REFERENCES

[1] Maria Raquel Oliva and Sanjay Saini," Liver cancer imaging: role of CT, MRI, US and PET", Cancer Imaging (2004) 4, S42–S46 DOI: 10.1102/1470-7330.2004.0011

[2] Shelhamer E, Long J, Darrell T, "Fully Convolutional Networks for Semantic Segmentation", IEEE Transactions on Pattern Analysis and Machine Intelligence (2017) 39(4) 640-651

[3] Park S, Seo K, Park J, "Automatic Hepatic Tumor Segmentation Using Statistical Optimal Threshold", 1 Dept. of Biomedical Engineering, ICCS 2005, LNCS 3514, pp. 934 – 940, 2005

[4] Y. Rakesh Kumara, N.Moorthy Muthukrishnana , Abhishek Mahajanb , P. Priyankaa , G. Padmavathia , M. Nethraa , R. Snehaa Meenakshi H Thakurb ," Statistical Parameter-based Automatic Liver Tumor Segmentation from Abdominal CT Scans: A Potiential Radiomic Signature", 6th International Conference On Advances In Computing & Communications, ICACC 2016, 6-8 September 2016, Cochin, India

[5] Zhongliang Xue, Ping Li, Liang Zhang, "Multi-Modal Co-Learning for Liver Lesion Segmentation on PET-CT Images", DOI 10.1109/TMI.2021.3089702, IEEE Transactions on Medical Imaging

[6] JIA Tong, ZHAO Da-Zhe,WEI Ying,ZHU Xin-Hua,WANG Xu, "Computer-Aided Lung Nodule Detection Based on CT Images", 2007 IEEE/ICME International Conference on Complex Medical En2ineerin2

[7] Arifovic J, Genn Cay R, "Using genetic algorithms to select architecture of a feedforward artiÿcial neural network", (2001) 574-594

[8] Prerna Kakkar, "Computer-Aided Segmentation of Liver Lesions in CT Scans Using Cascaded Convolutional Neural Networks and Genetically Optimised Classifier", Arabian Journal for Science and Engineering https://doi.org/10.1007/s13369-019-03735-8

[9] G Rajesh Chandra, Dr.Kolasani Ramchand H Rao, "Tumor Detection in Brain Using Genetic Algorithm", 7th International Conference on Communication, Computing and Virtualization 2016

[10] Minakshi Sharma1 and Sourabh Mukharjee, "Brain Tumor Segmentation Using Genetic Algorithm and Artificial Neural Network Fuzzy Inference System (ANFIS)", Advances in Computing & Inform. Technology, AISC 177, pp. 329–339

[11] J. Dheeba a, N. Albert Singh b , S. Tamil Selvi c, "Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach", h. J Biomed Inform (2014), http://dx.doi.org/10.1016/j.jbi.2014.01.

[12] A.Amutha, Dr.R.S.D.Wahidabanu, "Lung Tumor Detection and Diagnosis in CT scan Images", International conference on Communication and Signal Processing, April 3-5, 2013, India

[13] Chen F, Liu, "Three-Dimensional Feature-Enhanced Network for Automatic Femur Segmentation", IEEE Journal of Biomedical and Health Informatics (2019) 23(1) 243-252

[14] Du-Yih TSAI and Nobutaka TANAHASHI, "Neural-Network- Based Boundary Detection of Liver Structure in CT Images for 3-D Visualization", Department of Electrical Engineering, Gifu National College of Technology, Motosu-gun, Gifu 50 1-04, JAPAN

[15] Mubasher Hussaina, Najia Sahera, and Salman Qadri, "Computer Vision Approach for Liver Tumor Classification Using CT Dataset", APPLIED ARTIFICIAL INTELLIGENCE 2022, VOL. 36, 2022, NO. 1, e2055395.

[16] Mostafa A, Fouad A, "CT liver segmentation using artificial bee colony optimization", Procedia Computer Science (2015) 60(1) 1622-1630

[17]Yongtao Zhang, Haimei Li, Jie Du, Jing Qin, Member, IEEE, Tianfu Wang, Yue Chen, Bing Liu, Wenwen Gao, Guolin Ma, and Baiying Lei, "3D Multi-Attention Guided Multi-Task Learning Network for Automatic Gastric Tumor Segmentation and Lymph Node Classification", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 40, NO. 6, JUNE 2021.

[18] N. Nanda, P. Kakkar, and S. Nagpal, "Computer-Aided Segmentation of Liver Lesions in CT Scans Using Cascaded Convolutional Neural Networks and Genetically Optimised Classifier," Arab J Sci Eng, vol. 44, no. 4, pp. 4049–4062, Apr. 2019, doi: 10.1007/s13369-019-03735-8.

[19] K.Mala, Dr.V.Sadasivam, "Wavelet based texture analysis of Liver tumor from Computed Tomography images for characterization using Linear Vector Quantization Neural Network", 1-4244-0716-8/06/$20.00 ©2006 IEEE.

[20] Khaled Alawneh, Hiam Alquran 2,3, Mohammed Alsalatie 4, Wan Azani Mustafa 5,6, Yazan Al-Issa 7, Amin Alqudah 7 and Alaa Badarneh, "LiverNet: Diagnosis of Liver Tumors in Human CT Images", Appl. Sci. 2022, 12, 5501.

[21] Amandeep Kaur a, Ajay Pal Singh Chauhan a, Ashwani Kumar Aggarwal, "An automated slice sorting technique for multi-slice computed tomography liver cancer images using convolutional network", 2021 Elsevier Ltd, vol. 42, no. 5, pp. 0957-4174, Aug. 2021, doi: S095741742101071.

[24] Almotairi S, Kareem, " Liver tumor segmentation in CT scans using modified segnet", Sensors (Switzerland) (2020) 20(5)

[25] Zhongliang Xue, Ping Li, Liang Zhang, "Multi-Modal Co-Learning for Liver Lesion Segmentation on PET-CT Images", 0278-0062 (c) 2021 IEEE.

[26] Zhao B, Schwartz L, "Shape-Constraint Region Growing for Delineation of Hepatic Metastases on Contrast-Enhanced Computed Tomograph Scans", Volume 41, Number 10, October 2006

[27] Massoptier L, Casciaro S, "A new fully automatic and robust algorithm for fast segmentation of liver tissue and tumors from CT scans", European Radiology (2008) 18(8) 1658-1665

[28] Sara Noor Eldin, Jana Khaled Hamdy, "Deep Learning Approach for Breast Cancer Diagnosis from Microscopy Biopsy Images", July 01,2021 at 19:58:50 UTC from IEEE Xplore

[29]Rania M. GhoniemA Novel Bio-Inspired Deep Learning Approach for Liver Cancer Diagnosis", jouernal of biomedicals, 31 January 2020

[30] D.Selvathi, C.Malini, P.Shanmugavalli, "Automatic Segmentation and Classification of Liver Tumor in CT Images Using Adaptive Hybrid Technique and Contourlet Based ELM Classifier", 2013 International Conference on Recent Trends in Information Technology (ICRTIT)