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DISCOVERY OF LIVER MALIGNANCE USING CONVOLUTION NEURAL NETWORK VARIANT

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ABSRACT

Right now, locating and detecting cancer tissue is a challenging and time-consuming procedure. Liver lesions can be segregated using cancer CT imaging to aid in treatment planning and clinical response monitoring. To segment hepatic tumours and tackle the present liver cancer issue, Mobile U-Net has been developed and is a useful tool. Liver lesion segmentation in CT scans can be utilised for therapy prediction, tumour burden assessment, and clinical outcome monitoring. This approach is a mobile device-specific modification of the U-Net architectural design. The idea is explained by the deep learning system by describing the characteristics that go into inner layer analysis and prediction and by exposing a portion of the decision-making process that pretrained deep neural network.
Keywords: *Malignance, Liver, CNN, MobileUNet*

1. INTRODUCTION

1.1 Liver Anatomy

The liver, one of the most significant organs in the digestive system, is shown to have two lobes. Although it does many things, one of its main responsibilities is to break down the nutrients that the small intestine receives. Furthermore, the liver secretes bile juice into the small intestine, aiding in the breakdown of fats. The body uses the raw materials absorbed by the gut to produce the chemicals it needs to operate as well as to rid the body of harmful poisons.

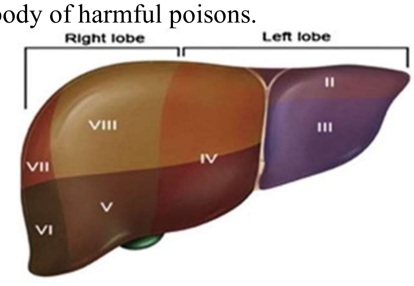

Figure 1.1: Anatomy Of The Liver

Based on statistical data, liver cancer ranks as the second most prevalent disease to take a person's life in men and the sixth in women. Roughly 750,000 people received a liver cancer diagnosis in 2008, and 696,000 of them lost their lives to the illness. Worldwide, the rate of male infection is double that of female infection. The highest rates of infection are seen in East and South-East Asia, Middle and Western Africa. Liver cancer is becoming more common worldwide, with a higher prevalence in the US and Central Europe. This may be due to obesity and the expansion of the Hepatitis C virus (HCV).). [2].

1.2 Current State of Liver Tumor Segmentation.

Usually, liver CT scans are read manually or partially manually. These methods, however, are very error-prone, arbitrary, costly, and time-consuming. Various computer-aided methods have been devised to circumvent these issues and improve the diagnostic precision of liver tumours.

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These systems were not very good at segmenting the liver and lesions because of a number of problems, such as the minimal colour contrast of the liver and surrounding organs, the different contrast levels in the tumours, the variable size and number of tumours, the abnormalities of the tissues, and the irregular expansion of the tumours in response to medical intervention. Therefore, a novel approach is needed to overcome these obstacles.

2. LITERATURE SURVEY

Bai et al. [6] presented the Multi-scale Candidate Generation (MCG) for the CT image-based liver tumour segmentation technique, which makes use of an active contour model and a 3D fractal residual network. The experiment's outcomes and comparisons with pertinent literature demonstrate that their complex system is capable of achieving a high level of segmentation efficiency. They have completed segmentation work on 3DIRCADb.

Das et al. [7] suggested the deep learning-based Watershed Transform and Gaussian Mixture Model (WT-GMM) for the diagnosis of liver cancer. For precise identification, this approach depends on marker-controlled watershed modification and the Gaussian mix model. Real-time clinical setup testing of the proposed technique is conducted using clinical data from a variety of patients. The deep-neural network classifier, which generated the highest precision of 99.38 percent with little validation loss, was the primary benefit of this automatic identification.

Grzegorz Chlebus et al.'s study [8] describes the use of 2D Convolutional Deep Neural Networks for the detection of liver lesions, followed by shape-based post-processing, which resulted in 77% accuracy and innovative discoveries for the LiTS challenge. With 87% accuracy, the Random-Forrest classifier was trained using the features generated by the Convolutional Neural Network in order to filter out False Positives.

In order to speed up training, Wen Li, Fucang Jia, and Qingmao Hu[9] reduced the noise reduction in CT scans by applying a Gaussian smoothing filter. The resulting pictures were then down-sampled and normalized. After the pre-processed pictures are sent to the CNNs, five CNNs with varying patch sizes are created: 13x13, 15x15, 17x17, and 19x19. The 17x17 CNN performed the best out of all the CNNs, making it the best option. FCN was utilised by Avi Ben-Cohen et al.[10] to segment the liver and find metastases on CT imaging. It proved to be a successful segmentation method. They conducted experiments using a small dataset of 20 individuals, each having a distinct 3D liver segmentation and an overall total of 43 livers and 68 lesions in a single slice. After cross-validation, they achieved positive and optimistic results for each patient, with a true positive rate of 0.86 and a false positive rate of 0.6. After data augmentation, two networks were trained: one for tumour and lesion segmentation, which used the output of the first network, and another for lever segmentation, which divided the liver's surrounding organs.

In order to autonomously separate the liver and lesions from abdominal MRI and CT images, Patrick Ferdinand et al.[11] proposed a technique that uses two cascaded fully convolutional neural networks (CFCNs). One CFCN is used to segment the liver itself, and the other model uses a clinical dataset for DW-MRI to detect lesions from the resulting Region Of Interest (ROI) of the first CFCN. Thirteen individuals underwent MR imaging and clinical assessment in order to establish the main diagnosis of HCC. In the MR-DWI, the Cascaded U-Net achieved an 87% dice score for liver. A lesion with a mean dice score of 69.7% was found.[12][13].

3. DEEP LEARNING MODELS

Among the Machine Learning family, Deep Learning draws inspiration from the biological nervous system, namely from the component responsible for communication and data processing. Deep learning encompasses a wide range of learning structures, such as deep neural networks. Learning can be done in supervised, semi-supervised, or unsupervised ways. Among many other applications, it is used in speech recognition, computer vision, natural language processing, and the analysis of medical pictures. The models of networks are:

- Convolutional neural network
- U-Net
- ResNet
- ResUNet
- MobileUNet

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are similar to neural networks in that they are composed of

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neurons. Numerous inputs are received by each neuron, which then computes the weighted sum of those inputs. The activation function then receives the result and produces an output in response. They have loss functions, just as neural networks. Unlike neural networks, CNNs function with volumes instead of vectors. They also include convolution layers, which are basically a group of separate filters together to produce the input image.

MobileUNet

Mobile U-Net is a variant of the U-Net architecture that was created specifically to be used on portable devices with limited computing capability. It was initially introduced in a research paper by Dai et al. titled "MobileUNet: A Lightweight Convolutional Neural Network for Medical Image Segmentation" that was released in 2018.

One common use of the U-Net architecture is the segmentation of organs or tumours in CT or MRI images. With its encoder-decoder structure, high-level features are extracted from the input image by the encoder by Downsampling, and the final segmentation map is created by the decoder through up sampling of these features.

Mobile U-Net employs a similar encoder-decoder architecture, but makes a number of modifications to reduce the model's memory use and computational complexity. Specifically, it uses depth-wise separable convolutions to separate the spatial and channel-wise convolutions and point-wise convolutions to reduce the number of channels in the feature maps. Additionally, residual connections are used to enhance training stability and aid in gradient flow.

In medical image segmentation tasks, the Mobile U-Net architecture has shown encouraging results, while being less efficient than the original U-Net. Its application has also proven beneficial for other computer vision issues including semantic segmentation and object recognition. When it comes to medical picture segmentation tasks, Mobile U-Net employs residual connections, depth-wise separable convolutions, and pointwise convolutions to minimise memory use and computational complexity of the U-Net architecture without sacrificing accuracy. Depth wise separable convolutions are convolutional layers that divide the spatial and channel-wise convolutions. The model is therefore more computationally efficient and has fewer parameters. Depth-wise separable convolutions are used by the encoder and decoder of the Mobile U-Net network.

Pointwise convolutions are used to reduce the number of channels in the feature maps. Compared to bigger convolutions, the computational cost of implementing them as 1x1 convolutions is significantly lower. Pointwise convolutions are employed in Mobile U-Net's encoder and decoder components subsequent to each depth-wise separable convolution.

Training stability and gradient flow are enhanced by residual connections. They work as connections that skip one or more tiers of the network. Relative connections are used in Mobile U-Net to link the encoder and decoder segments of the network.

4. EVALUATION PARAMETERS:

In this study, we assess the effectiveness of each learning model in terms of Accuracy, Dice coefficient, True Value Accuracy.

1. Accuracy

2. Dice Coefficient

3. Sensitivity

4. Efficiency

5. METHODOLOGY

5.1 Proposed Model

In this project, deep learning techniques will be applied to a dataset in order to identify the liver tumour. Using a fully convolutional neural network, the liver and the tumour will be divided. Two MobileUNet will be used: one for segmenting the liver and extracting ROI, and another for segmenting the tumour using the ROI that has been extracted.

The LITS-provided dataset of patient CT scans was used to train the learning models. The dataset was preprocessed to create subsets for the training, validation, and testing sets. A number of significant metrics, such as accuracy, dice coefficient, confusion matrix, and true value accuracy, have been used to evaluate the performance.

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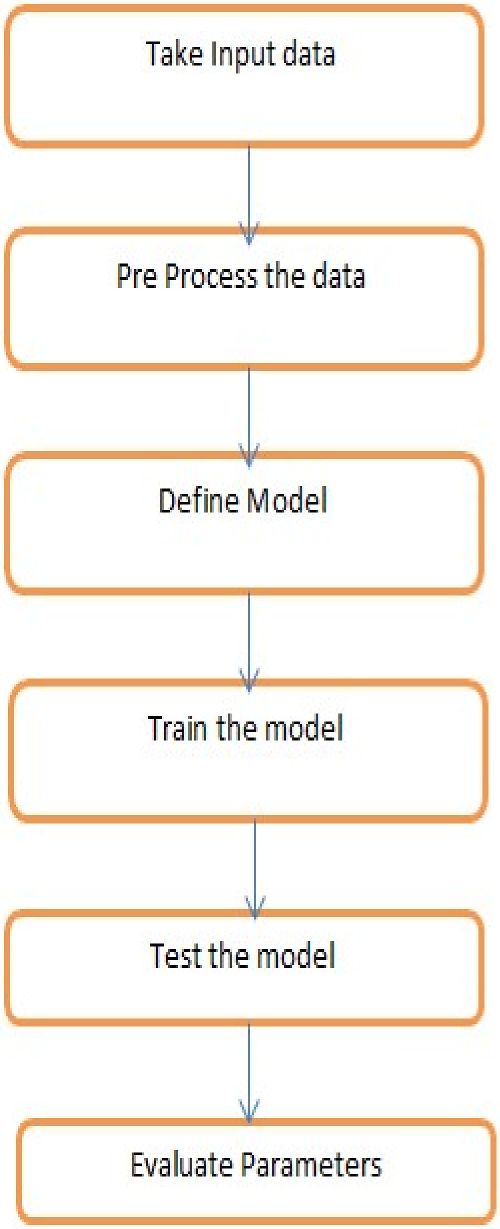

Fig 5.1 Proposed Models.

5.2 Steps Involved

Mobile U-Net can be used for liver tumor segmentation in several steps, which involve preparing the data, training the model, and using it for inference. Here is a step-by-step explanation of how to segment liver tumours using Mobile U-Net:

1. Prepare the data:
2. Preprocess the data:

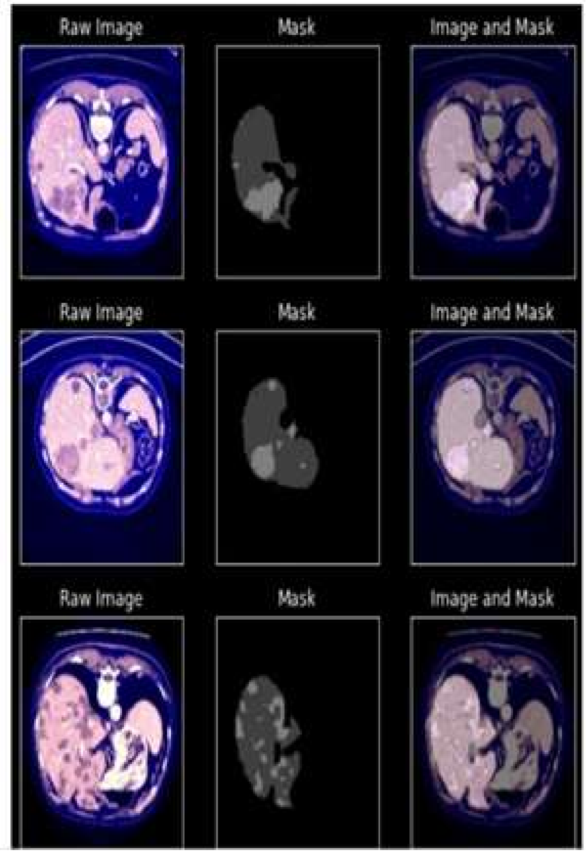

Figure 5.2 preprocess the data

3. Define the model:
4. Train the model:
5. Evaluate the model:

Efficient computation:

Mobile U-Net was designed to be computationally efficient and has fewer parameters than earlier segmentation systems. This makes it especially useful in situations when resources like memory and processing power are scarce, such as in applications involving the segmentation of medical pictures.

High accuracy:

In tasks involving medical picture segmentation, Mobile U-Net may retain exceptional accuracy despite its decreased complexity, frequently outperforming more complicated designs.

Real-time performance:

Importantly, Mobile U-Net enables real-time performance in medical photo segmentation applications because to its efficient computation and minimal memory utilization. for uses like

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image-guided surgery, among others.

Transfer learning:
The mobile U-Net leverages pre-trained weights from other U-Net models in order to benefit from transfer learning because it is an adaptation of the U-Net architecture. This might significantly speed up training and improve accuracy, particularly if there is a restricted quantity of the training set.

Low memory usage:
By utilising depth-wise separable convolutions and pointwise convolutions, Mobile U-Net significantly reduces the number of parameters and memory use compared to earlier designs. This enables it to function on mobile devices with limited memory, such as tablets and smartphones.

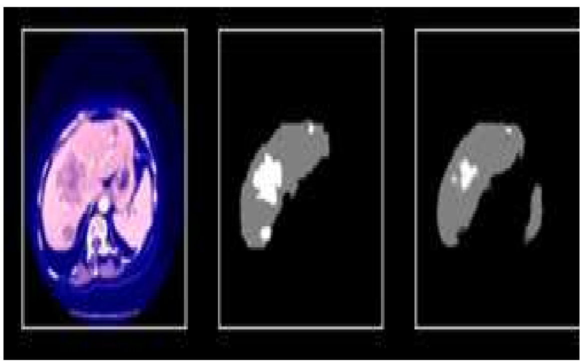

Figure 5.3 Segmentation Outcomes

The performance of the liver segmentation algorithm was evaluated using several performance metrics. The segmentation output of the algorithm and the accompanying ground truth images are included on this page. The segmentation outcome of this network on the segmentation of liver cancers from the liver and straight from the abdominal CT scan photos was assessed using several performance criteria.

6. CONCLUSION

This paper proposed an approach that starts with the UNet architecture and segments the liver and tumours. To improve segmentation performance and simplify the network, the number of filters and network layers were adjusted on the original UNet architecture. A unique method for class balancing is also offered to mitigate the problem of class imbalance. As a result, the system became more efficient and generated better segmentation outcomes. However, it had difficulty segmenting asymmetrical tiny tumours.

In general, Mobile U-Net has great potential as a liver tumour segmentation tool because to its ability to be tailored for usage on mobile devices with constrained processing resources, all the while retaining superior accuracy in medical picture segmentation tasks.

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