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EMPIRICAL INVESTIGATIONS TO DETECTION OF LIVER CANCER USING MOBILEUNET

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ABSTRACT

Identification of cancer tissue and biopsy is a procedure which is nevertheless however a delicate and complex process as of now. Cancer CT images can be segmented in order to help with the medical plan interventional and clinical response assessment of liver lesions. Mobile U-Net, which has been shaped and implemented as a reliable tool, is used for the segmentation of liver tumour and to address the existing liver cancer problem. Liver lesions in Computerized tomography may be used for assessing the volume and location of tumours, predicting their treatment and assessing condition of the patient. This is the amendment of the U-Net model structural design which takes been designed specifically for the usage in mobile platforms. The deep learning structure decodes the perception both by putting some enlightenment on what characteristics are involved in internal layer examination and forecast and by illuminating the part of a working model of a trained deep neural networks beforehand.
Keywords: *Deep learning ,U-Net, Mobile Optimization, Liver Tumor segmentation, Computed Tomography*

1. INTRODUCTION

1.1 Anatomy of the Liver

Without a doubt, one of the most important organs in the digestive system is the liver and it has got two lobes as depicted here. It has a number of functions with the most evident being that of digesting the nutrients that the small intestine assimilates. Also, the small intestine is given bile juice coming from the liver for digestion of fats. In addition to synthesizing the necessary chemicals the body needs to operate, it also takes the materials absorbed by the intestine and purges the blood stream of dangerous toxins.

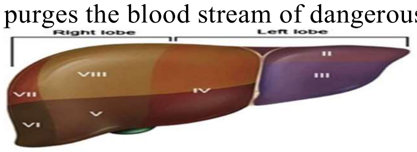

Figure 1.1: The Liver's Anatomy

1.2 Stages of Liver Tumors

According to reports, liver cancer ranks sixth among women and second among men in terms of cancer-related deaths. Additionally, according to data from 2008, there are roughly 750,000 new cases of liver cancer identified year, and 696,000 people pass away from the illness.. I Male transmission rates are twice higher than the female ones across the world. Middle and Western Africa are mainly affected and among the Asian region, East and South East Asia are the most affected. Incidence of this condition is high within the global community especially in the US and Central European region: mortality rate of liver cancer is on the rise, which could be attributed to obesity as well as the distribution of HCV. [2].

Figures 1. 2, 1. 3, 1. 4, and 1. 5 illustrate each stage of liver tumors as well as the different therapy and diagnostic measures obligatory in collectively phase [3].

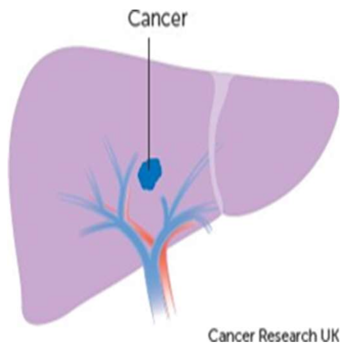

Figure 1.2: Stage 1A Of Hepatic Cancer

1.3 CT The computed tomography

After the discovery of computer tomography in 1970s most diagnosis procedures have been affected by the CT scanning. It enhanced the ways of monitoring the cardiac condition, operations, cancer identification and damages treatment. It got rid of exploratory surgeries as a norm. [4].

Not like conventional x-ray and CT equipment, the latter has a motorized x-ray source attached to the scanner. Housing or a tower is centered on a revolving motorized base or source in case of a gantry. Thus, during the examination, the patient lies on a bed that is mounted on a rail installed on the ceiling and The patient is rotated by the x-ray tube.. CT scanners transmit the data that ordinary x rays use film plates for detection instead of films.

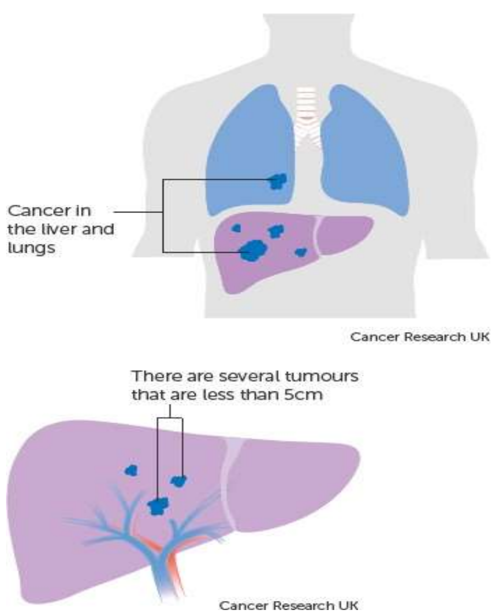

Figure 1.3: Stages 2A And 2B Of Hepatic Cancer

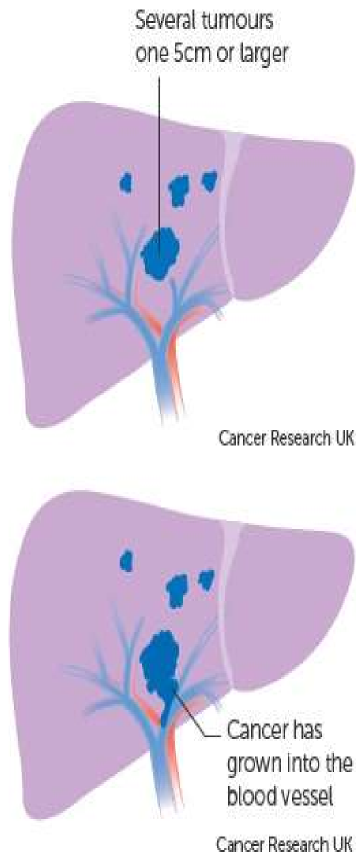

Figure 1.4: Stages 3A And 3B Of Hepatic Cancer

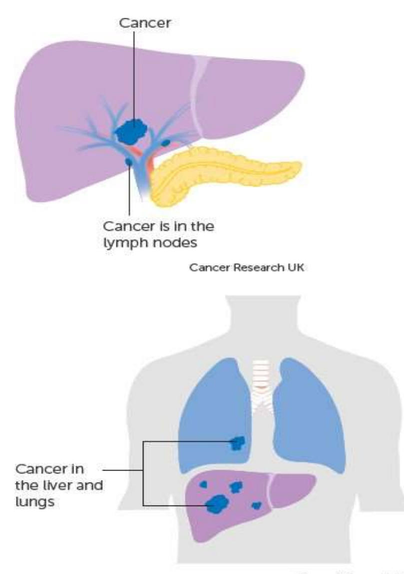

Figure 1.5: Stages 4A and 4B of Hepatic Cancer

whereby the data was input to a computer which produced a two dimensional utilizing information obtained from one of these rotations, an image slice of the patient. By revolving the prototypical in astronomical and looking at the slices one after another the computer can also allow to create a model of the patient in 3D showing all the scanned organs and showing to the medical personnel the exact place where the problem is. [5]

1.4 Condition of Liver Tumour Division

CT scans of the liver are normally reviewed or analyzed either via reviewing the image manually or by semi-automated approach. But each of these methods is arbitrary, expensive, time-consuming, and prone to making mistakes. With the use of computers, numerous methods that address these issues have been developed to enhance the liver tumour's diagnostic potential. Because of these factors like nearby organ, color contrast distinct contrast level in malignancies between the liver and the liver and the tumors
, multiple and small size of tumors, These techniques were not as successful in separating the liver from the lesions due to the uneven growth of the tumors in response to the medication intervention and the irregularities in the tissues.

Therefore, it calls for a new approach to overcome these obstacles.

1.5 Objective

The main aim is to perform segmentation of the liver and to perceive the lesion in the liver.

- The main focus is therefore to develop an application that will helpful in the segmentation of the lesion found in the liver using MobileUNet.

- Hence, it is possible to state that with the help of this model it is easier to enhance the accuracy as well.

2. LITERATURE SURVEY

In the paper [6], an active contour model and a 3D fractal residual network were used to support MCG for the CT image-based liver tumour segmentation. They have a pretty advanced system and based on the results of the experiment as well as comparisons with other research they made one can conclude that their system has a potential for very high segmentation efficiency. They have done 3DIRCADb segmentation jobs There are different types of segmentation but they have done job of the following type.

- Watershed transform used in combination with Gaussian mixture model (WT-GMM) was suggested by Das et al. , Liver cancer diagnosis by deep learning [7].

Marker-controlled watershed change is used in this method along with the Gaussian blend model for identification of microcalcification. The suggested method makes use of clinical data collected from a range of patients for the real-time clinical setup testing. The main use of this automatic identification was the deep neural network classifier, which provides 99.38 percent analytical accuracy, as the highest available of which there is little or no validation loss.

Grzegorz Chlebus et al. [8] discusses the detection of liver lesions by means of 2D Convolutional Deep Neural Networks that produced state-of-the-art outcomes for the LiTS challenge, including 77% accuracy after shape-based post-processing. With 87% accuracy, the Random-Forest classifier was utilized to filter False Positives after being trained on CNN features.

- Three modifications were made by Wen Li,9] including reduction of the noise through putting the CT scans through a Gaussian smoothing filter, normalization and down sampling of the result images to reduce training time. Next, the photos are sent into CNNs. 5 CNNs of different patch size were developed 13 x 13, 15 x 15, 17 x 17, 19 x 19, but 17 x 17 was found to be superior in giving better results to any of the other CNNs.
- In order to partition the liver and identify metastases using Computed Tomography (CT) scans, Avi [10] used FCN. This I found to be a good way of segmenting the market. They did it on a reduced-size set of 20 people and every person has a 3D liver segmentation43 livers and 68 lesions overall in one slice. It also had zero false negative rate and has a sensitivity level of 0.86 percent for true positives and 0% for false positives, or six per patient., they got good and promising results as verified through cross validation. Two networks were trained once the data was augmented: one for lever segmentation.which help in separating the organs adjacent to the liver and another that uses the first network's output for the segmentation of tumors and lesions.

Patrick. [11] developed a technique that incorporates a pair of CFCNs that can work independently to identify the liver and lesions from CT and MRI scans of the abdomen which one of the two was utilized for the segmentation of the Liver itself, with the other models detecting lesions from the resulting data by using a clinical dataset for DW-MRI

ROI of the initial CFCN For making the primary diagnosis of HCC of 31 patents, clinical evaluation and MR imaging were done. The proposed Cascaded U-Net for segmenting liver in MR-DWI was also effective achieving 87% dice score. We identified the presence of a lesion which had a mean dice score of 70%.

Mohammed [12] put forward a new algorithm for 3D Segmentation which is fused from a localized contouring algorithm and a newly designed k-mean algorithm. In the Segmentation step of this method the program identifies five distinct regions in the CT scans, when used with the 3D rendering the method was efficient and precise with the mean accuracy rate of 98%. 27%

In 2017, another way of segmenting medical image was being offered by Fausto Milletari FCNNs. In order to process MRI Volumes, the FCN was provided with extensive training. However, rather than slice-wise preprocessing the input volumes they used volumetric convolutions. Instead, they introduced a new measure – deep learning-based objective formula that calculates the maximum Dice coefficient. They were precise and quick in identifying on the MRIs of the prostate.

Yunhong Wang, Qingjie Liu, and Zhengxin Zhang [20] collaborated on Road extraction from aerial photos, a basic remote sensing operation, is difficult because of noise extracted from the images. Road extraction has several uses, including updating geographical data, creating maps, and navigating unmanned vehicles. After finding that using the U-Net paradigm did not yield the optimal results, they built a new model called ResUNet. This model combines the best features of the ResNet and U-Net models. ResUNet enables faster training with less data by using residual blocks that use skip-connections as opposed to the conventional convolutions that the standard U-Net uses.

2.1 Research Gaps

The Gaussian mixture model uses fewer CT scans overall and less calculation to calculate the work's computational complexity. By taking into account the 3D volumetric image visualization for tumour identification

, the procedure can be further enhanced. The main drawback of this type is that. The boundaries of tumours cannot be precisely segmented in Multi-scale Candidate Generation (MCG), because numerous nearby tumours may be segregated into a single tumour location. Instead of accurately segmenting the tumour, these models mainly concentrated on tumour detection.

2.2Problem Statement

Generally speaking, organ tissue collection can be used to identify malignancy. The difficulty here is that there is a potential that cancer cells will spread when tissues are collected using medical techniques, it makes the illness worse. Now this initiative, we partition the in an effort to reduce risk.

CT scans are useful for both planning therapies and tracking clinical outcomes. The Gaussian mixture model uses fewer CT scans overall and less calculation to calculate the work's computational complexity. Convolutional neural networks are utilised to get around these problems and raise the accuracy of liver cancer diagnosis. These networks have demonstrated strong performance in face recognition and image classification. Generally speaking, Pixel levelling in an image may be done quickly and easily with deep learning.

For pre-processed photos, the nature of the retrieved characteristics determines how precisely the work must be completed, and the mined images might thus mirror the properties of the images themselves [21]. Our target is to build a CNN model to In MobileUNet, segment the liver, use the Region of Interest, and find

2.3 Dataset

A baseline used to segment liver tumors is LiTS17. Many clinical locations throughout the world contribute data and segmentations. The training data set has 130 CT images, while the test data set contains 70. Both the training and test situations included representations of abdominal CT images.

2.4 Models of Deep Learning

Deep Learning, one of the Machine Learning family's models, is inspired by the communication and data processing sections of the organic nervous system. Many different learning architectures, including deep neural networks, are included in the category of deep learning. There are three types of learning: semi-supervised, unsupervised, and supervised. Among the many other applications are speech recognition, computer vision, natural language processing, and medical image analysis.

The prototypes of networks are:

- MobileUNet
- ResUNet
- U-Net

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- ResNet
- CNN

2.4.1Convolutional Neural Network

In that they are made up of neurons, CNNs are comparable to neural networks. Each neuron receives many inputs and calculates the inputs' weighted total, before feeding the result to the activation function, which responds by producing an output. The same as neural networks, they too have loss functions. CNNs operate on volumes rather than vectors, in contrast to neural networks. Convolution layers are also included in them; these are essentially several different filters put together to create the input image.

2.4.2 U-Net Architecture

The below figure depicts the network architecture. It is made up of two paths: one that contracts and one that expands and contains a total of 23 convolution layers [18]. Every stage of the Contracting Path utilizes the same standard CNN architecture, which includes of: A ReLU is the unit that comes after each convolution. For additional information about ReLU, see figure.

• A maximum 2x2 pooling operation with a 2 stride. For additional information about ReLU, see figure.

• There are twice as many feature channels when down sampling is used. Up sampling the feature map, a 2x2 convolution that cuts feature map sizes in half, concatenation with the cropped feature map, two 3x3 convolutions, and the ReLU activation function comprise each stage of the Expansive Path. [24]

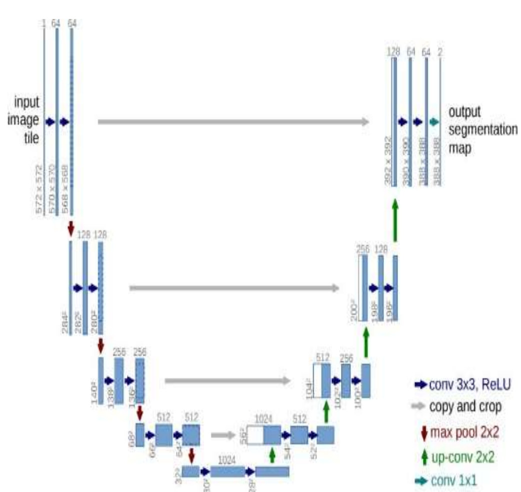

Figure 2.1: The U-Net CNN's architecture

U-Net Limitations

Despite the fact that U-Net's Liver Segmentation findings were quite good figures [24] and, it produced negative results on the Tumor Segmentation where we got empty resulting mask. After searching and trying we found the ResUNet model which is a hybrid between the U-Net and ResNet models.

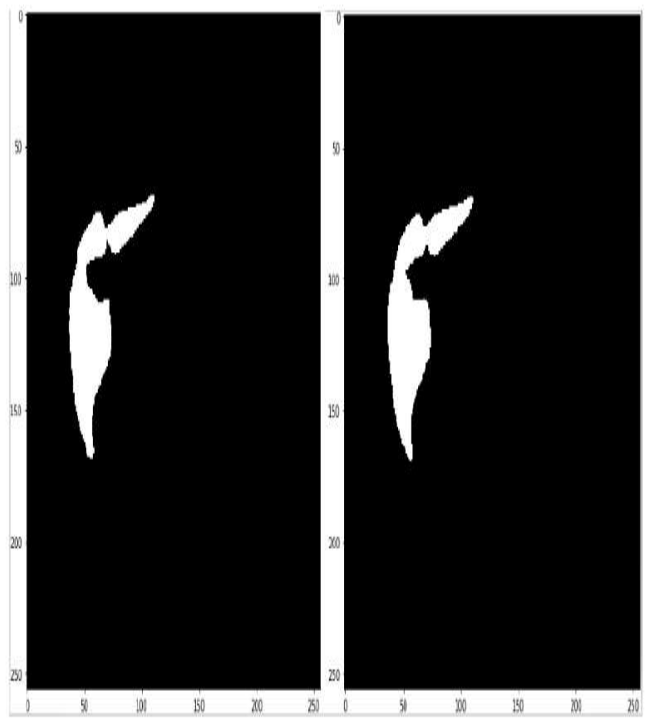

Figure 2.2: Random sample #1

The U-Net model's segmentation result is displayed in the above figure. The True input value is on the left, while the model's projected label is on the right.

2.4.3ResNet

ResNet is similar to standard Artificial Neural Networks but adds a little alteration known as Residual Blocks to the typical architecture. Residual Blocks, the primary structural component of ResNet, make use of a crucial idea known as Skip Connections. Connecting a layer with a successor layer of its successor layer is the basic goal of Skip Connections.By employing fewer layers during the first training stages, layer skipping lessens the Vanishing Gradient problem's effects. This simplifies the network and accelerates

learning because Less layers exist for information to travel through. The remaining blocks adjust [25] to, following learning, enhance the skipped layer and mute the upstream layer the weight by reusing the activation function from earlier levels.
ResNet typically only bypass one layer, However A weight matrix can be added to skip more than one and then are called HighwayNets.

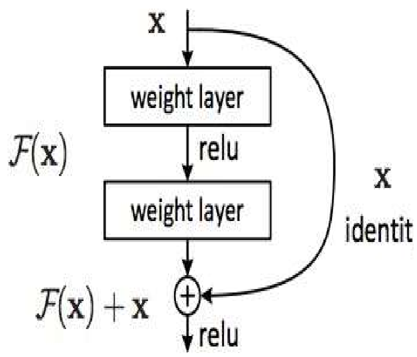

Figure 2.3: Residual block

2.4.4 ResUNet

By substituting residual blocks for convolutional ones in the classic U-Net and ResNet models, it incorporates the best features of both models. The CNN can be trained more easily using the residual unit since it needs fewer training parameters. Additionally, it can avoid degradation during the transmission of information within the residual unit and omit links between the network's low and high levels.

Three pathways make up the ResUNet. The three steps in the process are encoding, which condenses the input into a compact representation; decoding, which groups the representation according to pixels in the opposite way of encoding; and the bridge, which joins the two channels., are the three possible courses of action. Every path is constructed in Relative Units. [23]

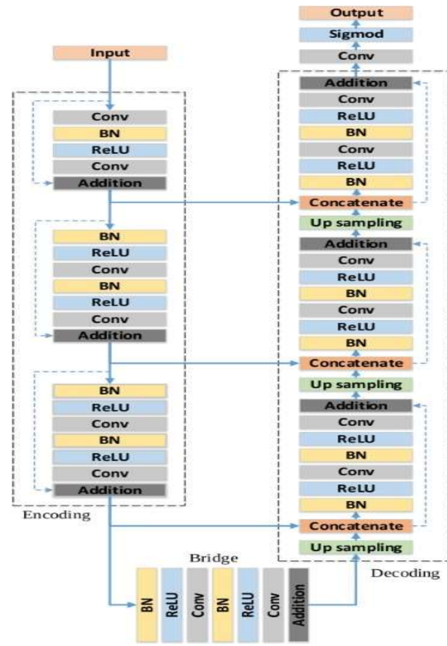

Figure 2.4 ResUNet

2.4.5 MobileUNet

A version of the U-Net architecture called Mobile U-Net has been specially designed for use on mobile devices with limited computing capacity. The term "MobileUNet: A Lightweight CNN for Medical Image Segmentation" was first used in a research article by Dai et al. published in 2018.
The division of tumors or organs in CT or MRI pictures is a typical job for which the U-Net design is employed. It utilizes an encoder-decoder structural attachment where the encoder condenses the input image to gain the high level features while the decoder extends these features in every direction to produce the end result, which is the segmentation map.

Similar encoder-decoder architecture is used by Mobile U-Net, but with various adjustments made to lower the computational complexity and memory consumption of the model. In particular, it divides spatial and channel-wise convolutions using depth-wise separable convolutions, and it minimizes the number of channels in the feature maps using point-wise convolutions. Also, leftover relationships are employed to facilitate gradient flow and enhance the stability of the training phase.

While being more effective than the original U-Net, the Mobile U-Net design has demonstrated promising results in medical picture segmentation tasks. Other computer vision problems, such object

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detection and semantic segmentation, have also benefited from its use.

Mobile U-Net works by using depth wise separable convolutions, pointwise convolutions, and residual connections to diminish the computational complexity and memory usage of the U-Net architecture while maintaining high accuracy in medical image segmentation tasks.

Depth wise separable convolutions can be defined as convolutional layers which are characterized by segmenting the spatial convolutions and channel wise convolution.. As a result, the model has fewer parameters and is more computationally efficient. The encoder and decoder of the Mobile U-Net network use depth-wise separable convolutions.

Using pointwise convolutions, the feature maps' channel count is decreased. They are implemented as 1x1 convolutions, which have a much smaller computational cost than larger convolutions. In Mobile U-Net, pointwise convolutions are used after each depth wise separable convolution in the network's encoder and decoder components.

Residual connections are used to help with gradient flow and improve training stability They function as skip connections that omit one or more network levels.. In Mobile U-Net, residual connections are used to connect the encoder and decoder parts of the network.

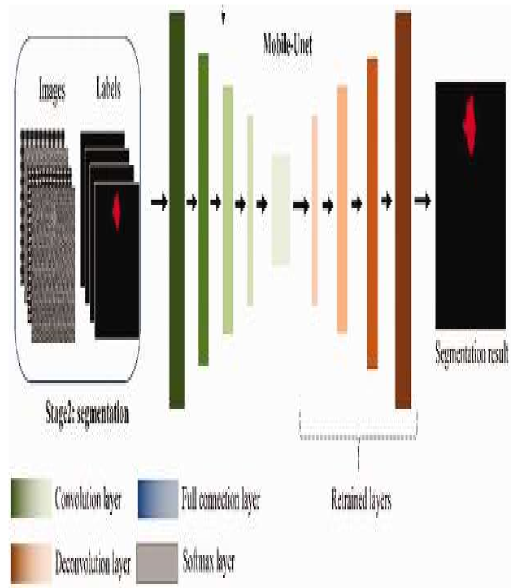

Figure 2.5 Mobile Unet Architecture.

Topology of the encoder-decoder in the Mobile U-Net architecture is comparable to that of the original U-Net design. The encoder component is made up of many layers of depth wise separable convolutions and max pooling operations, while the decoder part consists of several layers of up sampling and concatenation operations followed by depth wise separable convolutions.

In order to link the relevant layers in the encoder and decoder portions at each step, skip connections are used. The skip connections enable the decoder to utilize the encoder's low-level characteristics to increase the segmentation's accuracy.

It has been demonstrated that Mobile U-Net performs medical picture segmentation tasks well and is more productive than the original U-Net. Other computer vision problems, such object detection and semantic segmentation, have also benefited from its use

2.5 Parameters for Evaluation

In this study, we evaluate the performance of each learning model with respect to the Accuracy, Dice Coefficient, and True Value Accuracy metrics.

Accuracy

Without taking into account the class, accuracy measures how many pixels are properly categorized, which is a poor statistic as the true negatives value will always receive 95%+ and will always be in a dominant position.

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$$Accuracy = \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}}$$

--(1)

Dice Coefficient
It calculates the degree of overlap between the classes of the expected label B and the supplied label A.

$$Dice\ [17] = \frac{2 \times |(A \cap B)|}{|A| + |B|}$$

--- (2)

Sensitivity
The proportion of positives that are accurately classified as such is what is measured by sensitivity. Likewise referred to as True Positive Rate (TPR)

Sensitivity = (TP / (TP+FN)) * 100 --- (3)

- **Efficiency**

Efficiency = (Sensitivity + Specificity + Accuracy) /3 – (4)

3. METHODOLOGY

3.1 Suggested Framework

In this work, a dataset will be subjected to deep learning algorithms in order to detect liver tumors. A FCNN will be used to separate the tumour and liver. We'll utilize two MobileUNet: one to segment the liver and extract ROI, and another to segment the tumour using the extracted ROI. The learning models were trained using the patient CT scan dataset that LITS provided. The dataset was pre-processed to create subsets for the training, validation, and testing sets.
The performance has been assessed using a number of important measures, including real value accuracy, confusion matrix, accuracy, and dice coefficient.

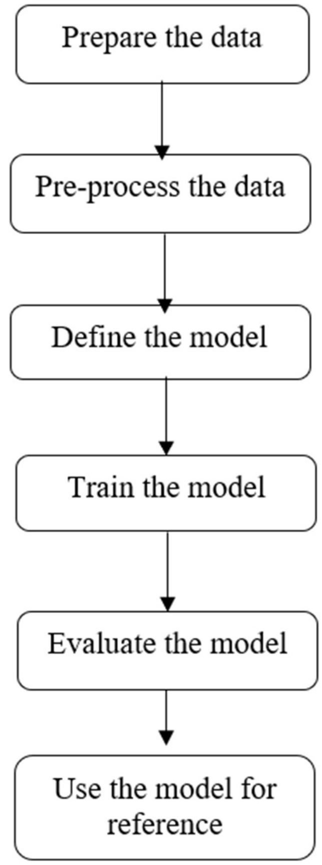

Figure 3.1: An Outline Of The Suggested Procedure

3.2 Steps Involved

There are multiple processes to employing Mobile U-Net for liver tumour segmentation: data preparation, model training, and inference. The following describes how to use Mobile U-Net to segment liver tumors step-by-step:

Prepare the data:
The dataset must first be ready for segmentation of liver tumours. This involves acquiring medical images of the liver and manually segmenting the tumors in the images. The dataset should include both the matching tumour segmentation masks and the input photos.
Preprocess the data:
Preprocessing the data is necessary before training the model, to normalize the pixel values, resize the images to a common size, and augment the data to expand the training set's size. Normalisation, resizing, and data augmentation methods including rotation,

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flipping, and shifting are a few examples of preprocessing procedures.

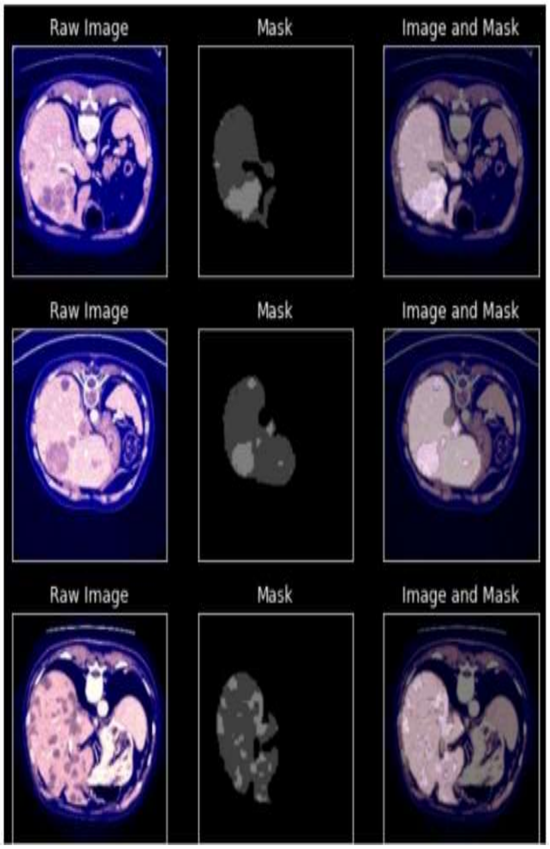

Figure 3.2.1 Preprocess The Data

- **Define the model:**
  The next step is to define the Mobile U-Net architecture for segmenting liver tumours. The structure should include an encoder part that down samples the input images and extracts high-level features, and a decoder part that up samples the features and produces the final tumor segmentation mask.
- **Train the model:**
  After defining the model architecture, the next step is in order to instruct the model using the preprocessed data. In an effort to lessen the difference between the predicted tumour segmentation masks and the ground truth masks, the model parameters are optimised throughout the training phase. Metrics like loss, accuracy, and dice coefficient may be used to keep track of the training process.
  Evaluate the model:
  The next stage is to assess the model's functionality with a test set of liver image data once it has been trained. This requires the calculation of characteristics such as the dice coefficient, sensitivity, specificity, and accuracy.
- **Use the model for inference:**
  After evaluating the model, the final step is to use it for inference on new liver images. This involves inputting a new liver image into the model and obtaining the corresponding tumor segmentation mask. The tumor segmentation mask can then be used to identify and analyze the tumor in the liver image.
  All things considered, Mobile U-Net can be an effective method for segmenting liver tumors., as it can be optimized for use on mobile devices with limited

  computational resources while maintaining outstanding accuracy in difficult medical image segmentation tasks.
  Mobile U-Net offers several advantages over other segmentation architectures, particularly in the medical image segmentation domain:
- **Efficient computation:**
  Mobile U-Net is specifically with fewer parameters than previous segmentation systems, it was created to be computationally efficient. This makes it especially beneficial for applications involving the segmentation of medical images, where tools like memory and computational power may be limited.
- **High accuracy:**
  Despite its reduced complexity, Mobile U-Net is able to maintain excellent accuracy in challenges involving medical image segmentation, often performing as well as or better than more complex architectures.
- **Real-time performance:**
  Because of its efficient computation and low memory usage, Real-time performance in medical picture segmentation tasks is possible with Mobile U-Net, which is crucial. for applications such as image-guided surgery.
- **Transfer learning:**
  Since an adaption of the U-Net architecture, mobile U-Net benefits from transfer learning by using pre-trained weights from other U-Net models. If there is a limited amount of the training set, this could greatly expedite training and increase accuracy.
- **Low memory usage:**
  In comparison to previous designs, Memory usage and the quantity of parameters are significantly reduced with Mobile U-Net. by using depthwise separable convolutions and pointwise convolutions. This makes it work

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with memory-constrained mobile devices like smartphones and tablets.

4. RESULTS :

Liver tumors development, segmentation, and segmentation using computed tomography Tumour candidates, multiscale candidates, and active contour classification methods. We suggested many machine learning techniques for classifying liver tumors. When dividing the liver and applying lesions, many CNNs have been established. For instance, The liver segmentation dataset is substantially larger than the lesion detection dataset. This data collection can only be segmented manually in 2D.Important when only a few training examples are available train necessary invariants and efficient networks feature. We use some metrics to evaluate the performance of our models, such as Accuracy and Dice coefficient, Efficiency, Sensitivity.We obtained the following outcomes after segmenting the Liver using the MobileUNet model.
Table 3.1 represents The MobileUNet model's coefficient results for the training and validation sets of liver segmentation data

Table 3.1 : Dice Coefficient Results

Epoch	Dice Coef	Valid Dice Coef
1	0.7488	0.3230
2	0.8266	0.8390
4	0.8682	0.8740
6	0.8859	0.6852
8	0.8997	0.9339
10	0.8996	0.8476
15	0.9242	0.8292
20	0.8379	0.9426
25	0.9548	0.8611
30	0.8634	0.8436
35	0.8607 0.8683 0.9187	0.7745 0.7751 0.9020
40	0.7488	0.3230
45	0.8266	0.8390
50	0.8682	0.8740

These are the results of our model-based assessment of an arbitrary selection from the validation set.

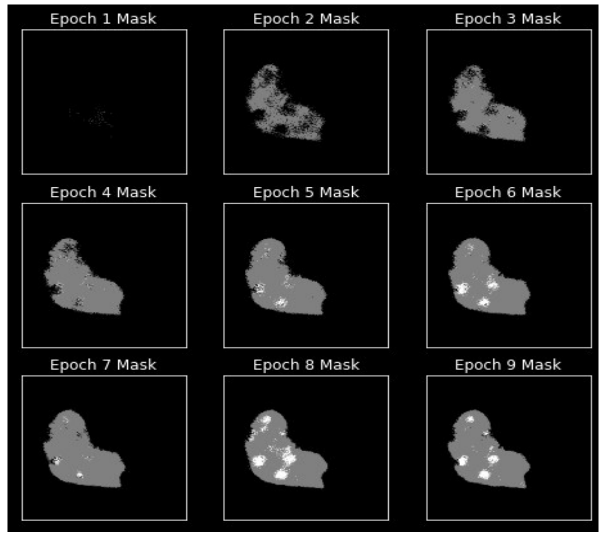

Figure 3.2.2 Segmentation Models

Different performance criteria were used to assess how well the liver segmentation algorithm performed. This page includes the algorithm's segmentation output together with the corresponding ground truth pictures.

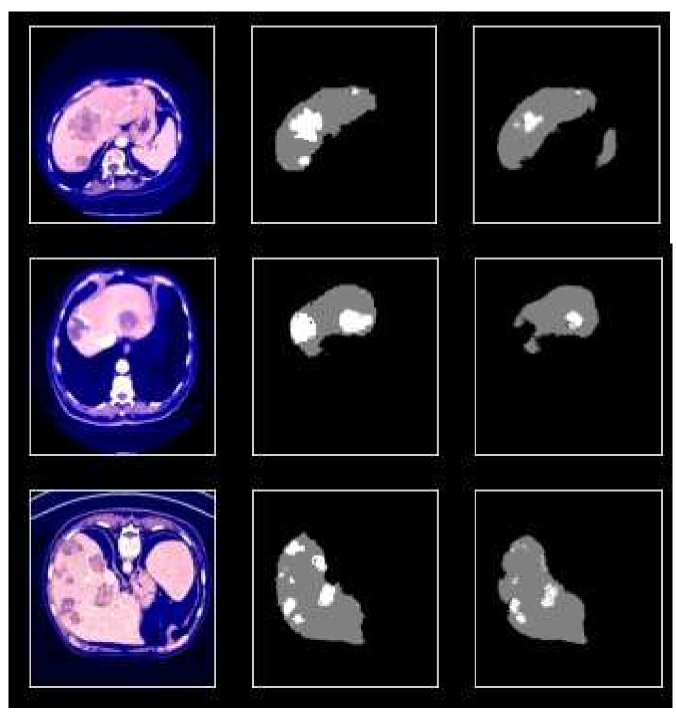

Figure 3.2.3 segmentation out comes

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Several performance parameters were used to evaluate the segmentation performance of this network on the segmentation of liver tumors from the liver and straight from the abdominal CT scan photographs.

5. INFERENCE AND FUTURE SCOPE

This work suggested a way for segmenting tumours and the liver utilizing the UNet architecture as a starting point. On the original UNet model, changes were made to the quantity of filters and network layers appropriate to simplify the network and enhance segmentation performance. To lessen the issue of class imbalance, a novel technique for class balancing is also presented. Through this, the system improved and produced better segmentation results. It had trouble segmenting small, asymmetrical tumors, though.

Overall, Mobile U-Net know how to be a powerful tool for liver tumor segmentation, as it can be optimized for use on mobile devices with limited computational resources while maintaining excellent accuracy in challenges involving medical image segmentation.

REFERENCES

[1] Sherif R Z Abdel-Misih and Mark Bloomston. Liver anatomy. *The Surgical clinics of North America*, 90:643–53, 08 2010.

[2] Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R. L., Torre, L. A., & Jemal, A. (2018). Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: a cancer journal for clinicians*, *68*(6), 394-424.

[3] Mustafa, N., Abdul Razak, N. H. S., Abu Talip Yusof, N., & Abdul Karim, M. S. (2020, December).

Development of Microwave Antenna for Cancer Treatment. In *International Conference on Innovative Technology, Engineering and Science* (pp. 127-136). Springer, Cham.

[4] Power, S. P., Moloney, F., Twomey, M., James, K., O'Connor, O. J., & Maher, M. M. (2016). Computed tomography and patient risk: facts, perceptions and uncertainties. *World journal of radiology*, *8*(12), 902.

[5] Carleton, P. F., Schachter, S., Parrish, J. A., Collins, J. M., Crocker, J. B., Dixon, R. F., ... & Lash, T. B. (2016). National Institute of Biomedical Imaging

and Bioengineering point-of-care technology research network: Advancing precision medicine. *IEEE journal of translational engineering in health and medicine*, *4*, 1-14.

[6] Bai, Z., Jiang, H., Li, S., & Yao, Y. D. (2019).

Liver tumor segmentation based on multi-scale candidate generation and fractal residual network. *IEEE Access*, *7*, 82122-82133.

[7] Praveen, S. P., Hasan, M. K., Abdullah, S. N. H. S., Sirisha, U., Tirumanadham, N. K. M. K., Islam, S., ... & Ghazal, T. M. (2024). Enhanced feature selection and ensemble learning for cardiovascular disease prediction: hybrid GOL2-2 T and adaptive boosted decision fusion with babysitting refinement. Frontiers in Medicine, 11, 1407376.

[8] Chlebus, G., Schenk, A., Moltz, J. H., van Ginneken, B., Hahn, H. K., & Meine, H. (2018). Deep learning based automatic liver tumor segmentation in CT with shape-based post-processing.

[9] Li, W. (2015). Automatic segmentation of liver tumor in CT images with deep convolutional neural networks. *Journal of Computer and Communications*, *3*(11), 146.

[10] Ben-Cohen, A., Diamant, I., Klang, E., Amitai, M., & Greenspan, H. (2016). Fully convolutional network for liver segmentation and lesions detection. In *Deep learning and data labeling for medical applications* (pp. 77-85). Springer, Cham.

[11] Goryawala, M., Guillen, M. R., Cabrerizo, M., Barreto, A., Gulec, S., Barot, T. C., ... & Adjouadi, M. (2011). A 3-D liver segmentation method with parallel computing for selective internal radiation therapy. *IEEE Transactions on Information Technology in Biomedicine*, *16*(1), 62-69.

[12] Milletari, F., Navab, N., & Ahmadi, S. A. (2016, October). V-net: Fully convolutional neural networks for volumetric medical image segmentation. In *2016 fourth international conference on 3D vision (3DV)* (pp. 565-571). IEEE.

[13] Yuan, Y. (2017). Hierarchical convolutional-deconvolutional neural networks for automatic liver and tumor segmentation. *arXiv preprint arXiv:1710.04540*.

[14] Chlebus, G., Meine, H., Moltz, J. H., & Schenk, A. (2017). Neural network-based automatic liver tumor segmentation with random forest-based candidate filtering. *arXiv preprint arXiv:1706.00842*.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[15] Han, X. (2017). Automatic liver lesion segmentation using a deep convolutional neural network method. *arXiv preprint arXiv:1704.07239*.

[16] Ben-Cohen, A., Klang, E., Kerpel, A., Konen, E., Amitai, M. M., & Greenspan, H. (2018). Fully convolutional network and sparsity-based dictionary learning for liver lesion detection in CT examinations. *Neurocomputing*, *275*, 1585-1594.

[17] Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention* (pp. 234-241). Springer, Cham.

[18] Praveen, S. P., Murali Krishna, T. B., Anuradha, C. H., Mandalapu, S. R., Sarala, P., & Sindhura, S. (2022). A robust framework for handling health care information based on machine learning and big data engineering techniques. International Journal of Healthcare Management, 1-18.

[19] Zhang, Z., Liu, Q., & Wang, Y. (2018). Road extraction by deep residual u-net. *IEEE Geoscience and Remote Sensing Letters*, *15*(5), 749-753.

[20] Zou, K. H., Warfield, S. K., Bharatha, A., Tempany, C. M., Kaus, M. R., Haker, S. J., ... & Kikinis, R. (2004). Statistical validation of image segmentation quality based on a spatial overlap index1: scientific reports. *Academic radiology*, *11*(2), 178-189.

[21] Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., ... & Zuiderveld, K. (1987). Adaptive histogram equalization and its variations. *Computer vision, graphics, and image processing*, *39*(3), 355-368.

[22] Hong, J. S., Kaneko, T., Sekiguchi, R., & Park, K. H. (2001). Automatic liver tumor detection from CT. *IEICE Transactions on information and systems*, *84*(6), 741-748.

[23]Tata Balaji, Kurra Upendra Chowdary, Dr. P Venu Madhav, Dr.A Geetha Devi, Mrs.T. Mahalakshmi, Dr.Surya Prasada, Rao Borra, N.Jaya, Pragmatic Investigations To Smart Dusts Location Appraisal Precisely Using Machine Learning, Journal of Theoretical and Applied Information Technology,102(18), pp. 6774-6781

[24] P.Ravi Kumar, Viswanadham Ravuri, Tata Balaji, Kiran Kumar Kaveti ,G Prasanna Kumar, Elangovan Muniyandy, N.Jaya, Discovery Of Liver Malignance Using Convolution Neural Network Variant, Journal Of Theoretical And Applied Information Technology,102(10), Pp. 5390-5395

[25] M V Ganeswara Rao,Lakshmi Manasa B, Balaji Tata, Dr. Karuna Arava ,Ane Ashok Babu, Praveen Tumuluru, N.Jaya, Hereditary Approach For Finest Dissection System For Web Data, Journal Of Theoretical And Applied Information Technology102(10), Pp. 5546-5558