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Liver Cancer Segmentation through Enhanced Feature Extraction and Mapping using Improved Transfer Learning Techniques

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Abstract: - The largest solid organ in the body is the liver. Numerous other vital functions it carries out include removing impurities from the blood flow, controlling blood coagulation, and maintaining healthy blood sugar levels. All blood leaving the intestines and stomach is directed to the liver as its final destination. Liver illness may be brought on by infections, inherited diseases, cancer, too many harmful substances, or other conditions. Medical experts estimate that 1.6% of men and women in India could be diagnosed with liver cancer at some time in their life. The interpretation of liver CT scans often involves semi-manual or manual techniques; however these techniques are costly, time-consuming, subjective, and prone to error. To improve the detection of liver cancer, these issues have been addressed and a number of computer algorithms have been developed. To create a fully automated method for quickly extracting liver tumours from CT scan images.

Keywords: - Liver Tumor, Liver Diseases, CT Scan, Feature Extraction, VGG19

1. Introduction

The liver is the body's largest solid organ. It performs hundreds of other crucial tasks, such as clearing contaminants from the blood supply, regulating blood clotting, and preserving healthy blood sugar levels. It is in the right upper abdomen, below the rib cage [1]. The liver has four lobes (as shown in fig.1): the right and left lobes, which are larger, and the caudate and quadrate lobes, which are smaller. The falciform (Latin for "sickle-shaped") ligament, which joins the liver to the abdominal wall, separates the left and right lobes. The eight segments of the liver's lobes, which are composed of thousands of lobules (little lobes), can be further split into. The common hepatic duct, which removes bile from the liver, is reached via a duct that emerges from each of these lobules.

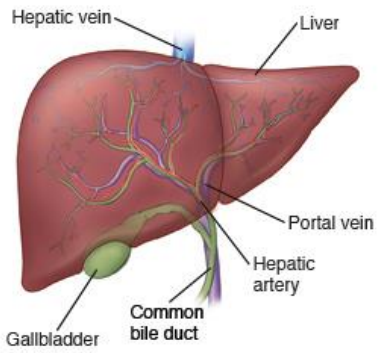

Figure: 1 Liver

The liver excretes a substance known as bile and controls the majority of blood chemical levels. This aids in removing waste from the liver. The liver is the final stop for all blood travelling out of the intestines and stomach. This blood is processed by the liver [2]. The nutrients are created, balanced, and broken down by it. Additionally, it transforms medications into forms that are simpler for the rest of the body to use. The liver is known to have more than 500 essential activities.

Some Major functions of Liver are:

- All of the blood in the body is filtered by the liver, which also detoxicates dangerous chemicals like alcohol and narcotics.
- Bile is a substance made by the liver that aids in fat digestion and waste removal.
- The liver is divided into four lobes, each of which has eight parts and thousands of lobules.

1.1. Liver Disease

Infections, hereditary conditions, cancer, or an excess of toxic substances can all cause liver disease. With the help of medicine or dietary modifications, healthcare professionals can successfully cure a variety of liver diseases.

Liver disorders come in a variety of forms [3]:

- Diseases brought on by viruses, including hepatitis A, B, and C

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- Diseases brought on by drugs, toxins, or excessive drinking. Cirrhosis and fatty liver disease are two examples.
- Liver tumor or cancer
- Inherited illnesses like Wilson disease and hemochromatosis

1.2. Liver Cancer

Cancer is a condition in which the body's cells proliferate unchecked. Liver cancer is the term for cancer that first appears in the liver as shown in fig. 2. One of the cancer forms with the quickest rate of growth in the World is liver cancer, which can be fatal. According to medical professionals, roughly 1.6% of men and women in the India may receive a liver cancer diagnosis at some point in their lives. Primary and secondary liver cancers are the two types [5]. Liver is the site of primary cancer. Secondary cancer can migrate from another area to liver.

Primary liver cancer comes in three different forms:

- Hepatocellular carcinoma (HCC): Accounting for almost all occurrences of liver cancer, this is the most prevalent kind.
- cholangiocarcinoma's subtype, intrahepatic cancer (IHC), is a liver cancer. IHC is bile duct carcinoma in the liver. It accounts for 10% to 20% of all cases of primary liver cancer.
- Angiosarcoma: Only 1% of primary liver cancer cases are of this extremely rare form. Your liver's blood cell lining is where this malignancy first manifests itself. (Other organs may potentially be impacted by angiosarcoma.)

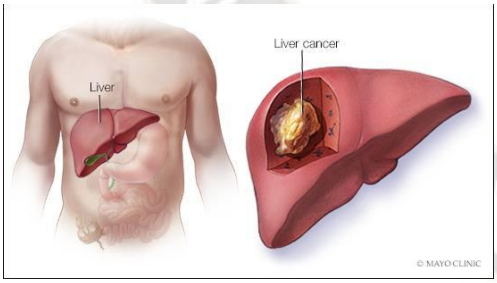

Figure: 2 Liver Cancer

Overall, it is estimated that HCC and IHC account for 2% of all new cancer cases and 5% of all cancer deaths in the India. HCC and IHC are frequently diagnosed and handled the same by medical professionals. Radiologists and oncologists utilise computed tomography (CT) or magnetic resonance imaging (MRI) to visualise the structure and texture of the liver. These anomalies are important biomarkers for early disease detection and progression in primary and secondary hepatic tumour malignancy [6].

Typically, semi-manual or manual methods are used to interpret CT scans of the liver, but these methods are expensive, time-consuming, subjective, and prone to error. These problems have been addressed, and a number of computation techniques have been created to enhance the detection of liver cancer. The low contrast between the liver and the surrounding organs, such as liver and tumours of different contrast values, changes in the number of tumours, the tumor's small size, tissue abnormalities, and irregular tumour growth, however, prevented these systems from segmenting and detecting liver lesions. To get around these challenges, a fresh strategy is required.

1.3. Contribution

This work has the following contributions:

- To designed a completely automated approach for extracting liver tumours from CT scan Images in a single pass.
- To design an improved feature mapping using dimensionality reduction technique t-SNE algorithm.
- To develop a generic model designed VGG19 with improved optimizer to handle sparse data.

The remaining part of the paper flows as follows. The literature on current study is presented in Section 2. Section 3 provides a description of the suggested approach. Evaluations of results for the proposed Improved VGG19 can be found in Section 4. Finally, Section 5 presents conclusion and future works follow.

2. Literature Review

In [6], study proposes a deep learning approach for early-stage liver disease prediction and classification based on non-alcoholic fatty liver disease. The approach uses 52 texture features, including grey level co-occurrence matrix and gradient co-occurrence matrix, and uses a deep neural network for feature prediction and classification. The study evaluates the predicted dataset using MRI images and datasets, comparing it with existing dominant methods, resulting in better results in comparison parameters. Early-stage liver disease prediction is crucial for health-related research, allowing for early treatment and prevention of various liver diseases.

In [7], study used Ostu preprocessing technique to enhance MRI images acquired from the internet. Marker-controlled watershed segmentation was used for segmentation, with some images achieving correct segmentation. Future work aims to create a GUI for single-click feature extraction using wavelet transform. Image processing, a mathematical operation, is used in medical applications for detection and treatment, including liver cancer cell detection. The

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technique enhances the MRI image and segments cancer cells using the watershed method.

In [8] study stated that Liver cancer is a rapidly growing and life-threatening disease, and early detection can reduce mortality rates. The study aims to develop a deep learning model using convolutional neural networks (CNNs) to help clinicians identify tumor types in liver regions. The model can transfer knowledge from pre-trained global models and decant it into a single model for diagnosing liver tumors from CT scans. The hybrid model achieved high accuracy, precision, and recall values, with a recall value of 0.979. Tested on limited data, the model can support specialist decisions and save time and effort in treating liver cancer, especially during annual examination campaigns. Proposed model of the study can also aid in supporting specialists' decisions and saving time during regular examinations.

In [9] a new method, the Hybridized Fully Convolutional Neural Network (HFCNN), has been proposed for liver tumor segmentation in CT images. This method is mathematically modeled to address the issue of liver tumors. HFCNN has been used for semantic segmentation in liver cancer analysis. The method enables the distinction between cancer and non-cancer lesions, requiring expertise and resources. The deep end-to-end ltumoursg approach helps differentiate between colorectal cancer metastases and benign cysts in abdominal CT images. The system demonstrates the importance of features in decision-making processes, highlighting the importance of illumination in deep learning systems.

In [10] it is stated that Liver tumour prediction is a challenging task in the medical field, requiring improved detection mechanisms for accuracy. Linear Discriminant Analysis (LDA) is used for feature extraction, as it can work with multiple classification algorithms and is better than logistic regression. A decision tree and Nave Bayes algorithm are supervised to predict the disease using identified parameters from LDA analysis. Simulation was conducted using Scikit in Python, and evaluation steps are discussed in the methodology and implementation sections.

In [11], proposes a cached CNN to improve image classification performance by classifying input images based on similarity with previously input images. The cached CNN extracts class labels and feature vectors from feature maps for images classified by the CNN, allowing for the output of a new image's class label based on its similarity with the cached feature vectors. This process can be performed at each layer, reducing the required classification time. Experiments were conducted to measure and evaluate the cache hit rate, precision, and classification time.

3. Transfer Learning Models

3.1. VGG16 Model

A ConvNet is another name for a convolutional neural network, which is a type of artificial neural network. An input layer, an output layer, and many hidden layers make up a convolutional neural network. One of the top computer vision models to date is the CNN (Convolutional Neural Network) variant known as VGG16 as shown in fig.3. This model's developers analysed the networks and enhanced the depth using an architecture with incredibly tiny (3 3) convolution filters, which demonstrated a notable advancement over the state-of-the-art setups. The depth was increased to 16–19 weight layers, yielding around 138 trainable parameters. The 16 convolutional layers of VGGNet-16 are quite appealing, and its architecture is very consistent. It has several filters but only 3x3 convolutions, like AlexNet. On 4 GPUs, it can be trained for two to three weeks. The community now views it as the best option for extracting characteristics from photos. The weight configuration of the VGGNet is openly accessible and has been employed as a standard feature extractor in numerous different applications and challenges. An overview of the VGG architecture is provided below: VGGNet is provided with a 224x224 picture as input. By removing a 224224 square from the centre of each image submitted for the ImageNet competition, the model's developers were able to maintain a constant image input size.

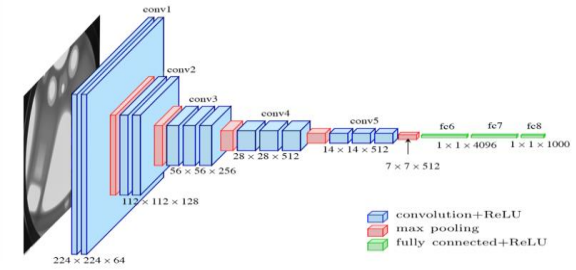

Figure: 3 VGG16 Architecture

3.2. VGG19 Model

VGG19 has layers that have already been trained and has a strong comprehension of the characteristics of a picture in terms of shape, colour, and structure. With 19 connection layers, comprising 16 convolutional layers and 3 fully connected layers, the VGG-19 is a deep learning neural network as shown in fig.4. Fully connected layers will classify the leaf images for those attributes after the convolution layers extract features from the input photos. In the network's image processing layers, it has three extra convolutional layers. These layers add greater variation for identifying high-level forms and objects and are added fairly deeply into the architecture. The convolutional layers that

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make up the VGG19 model are followed by a few dense, fully linked layers. With Include_top, you can specify whether or not you want the last dense layers. False means that the last dense layers are not yet put into the model.

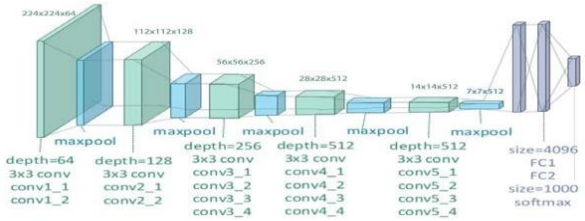

Figure: 4 VGG19 Architecture

3.3. Improved VGG19 Model (IVGG19)

The Fine tuned IVGG19 Model (as shown in fig. 5) has been proposed in this study for the identification and segmentation of liver tumors. Each neural network in the system has a training phase and a testing phase. During the training phase, various techniques known as feature extraction were obtained with the input CT Images. The expanded information, also known as input data, is then incorporated into the neural network system to produce a suitable framework. The testing of multiple convention layers in our feature extraction procedure has sought to identify a superior feature extraction network.

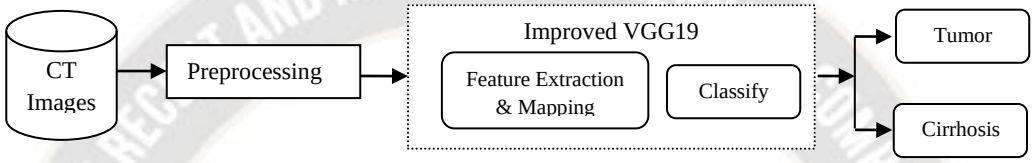

Figure: 5 Proposed Model

VGG19 Pre-Trained without top layer for fine tuning the model performance. Redefined the model with new top layers such as Fatten, 256-Dense (ReLU), Dropout (0.5), and 8-Dense (Softmax). Model uses Improved Optimizer ISDG, for every training example x (i) and label y (i), stochastic gradient descent (SGD) updates a parameter as follows in equ 1:

$$\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x^{(i)}; y^{(i)}) \text{ --- (1)}$$

This research improvise the optimizer by executing smaller updates (i.e., low learning rates) for parameters associated with frequently occurring features and bigger updates (i.e., high learning rates) for parameters associated with infrequent features, it adapts the learning rate to the parameters. This makes it a good choice for handling sparse data. In order to keep things short, we'll refer to the gradient at time step t as gt. The partial derivative of the objective function with respect to parameter i at time step is then gt,I in equ 2.

$$g_{t,i} = \nabla_\theta J(\theta_{t,i}) \text{--- (2)}$$

The SGD update therefore becomes: for each time step t, for each parameter I in equ 3:

$$\theta_{t+1,i} = \theta_{t,i} - \eta \cdot g_{t,i} \text{ --- (3)}$$

ISDG rule updates the general learning rate for each parameter i depending on the previously computed gradients at each time step t as shown in equ 4:

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\eta}{\sqrt{G_{t,ii}+\epsilon}} \cdot g_{t,i} \text{ --- (4)}$$

$G_t \in R^{dxd}$ is a diagonal matrix where each diagonal element i is the sum of the squares of the gradients with respect to i up to time step t and where is a smoothing term that prevents division by zero. Curiously, the method performs substantially worse without the square root function.

Next dimensionality reduction part has to be handled so to use it t-SNE algorithm used. A dimensionality reduction is accomplished through t-Distributed Stochastic Neighbor Embedding. This algorithm employs a randomized strategy to non-linearly reduce the dimensionality of the current dataset. The non-linear dimensionality reduction algorithm t-SNE identifies patterns in the data by comparing data points' similarity to features. The similarity of points is determined as the conditional probability that point A would select point B as its neighbor. First, the algorithm used in this method determines the joint probabilities between the data points, which describe how similar the points are to one another. The similarity between the data points is determined after the joint probability has been calculated and is based on the joint probability.

While t-SNE seeks to achieve the same by keeping similar data points together (and dissimilar data points apart) in both higher and lower dimensions, other dimensionality reduction algorithm seeks to minimise dimensionality by maximizing variance in the data. These factors allow t-SNE to significantly outperform than the other in terms of dimensionality reduction.

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4. Result and Analysis

Evaluating the performance of the model Loss rate and Accuracy is used. The proposed model IVGG19 compared with existing models such as VGG16 and VGG19.

Fig. 6 shows the performance of the VGG16 model on the Liver segmentation. 87% of accuracy attained but looks unstable and over fitted data.

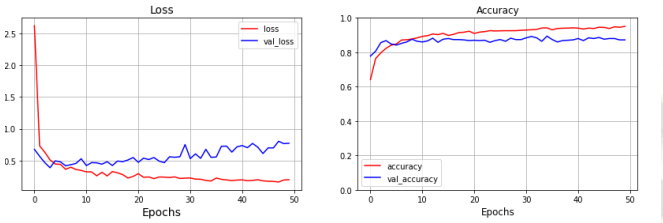

Figure: 6 Loss & Accuracy of VGG16- Training & Validation

Fig. 7 shows the performance of the VGG19 model on the Liver segmentation. Shows an improved rate of accuracy for 91% but still over fitted data.

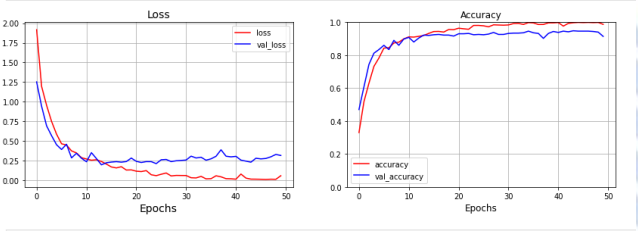

Figure: 7 Loss & Accuracy of VGG19- Training & Validation

Fig. 8 shows the performance of the proposed model IVGG19 on the Liver segmentation. It shows an improvement in accuracy of 97% and over fitting controlled.

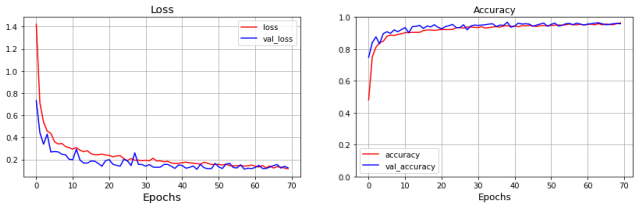

Figure: 8 Loss & Accuracy of IVGG19- Training & Validation

Based on the performance of the models the proposed IVGG19 selected for Liver Tissue detection and segmentation as shown in fig 9 & 10.

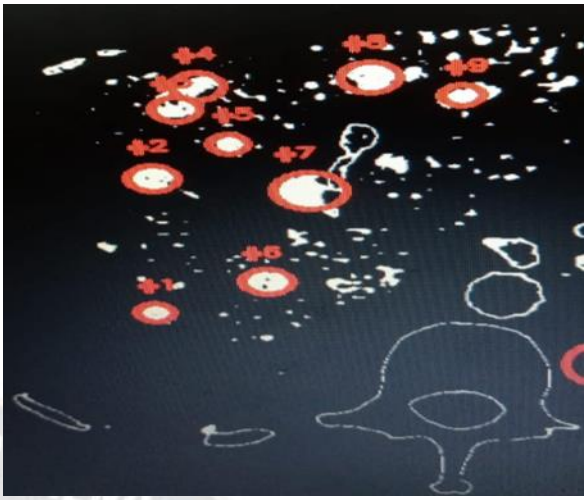

Figure: 9. Detected Liver Tissues

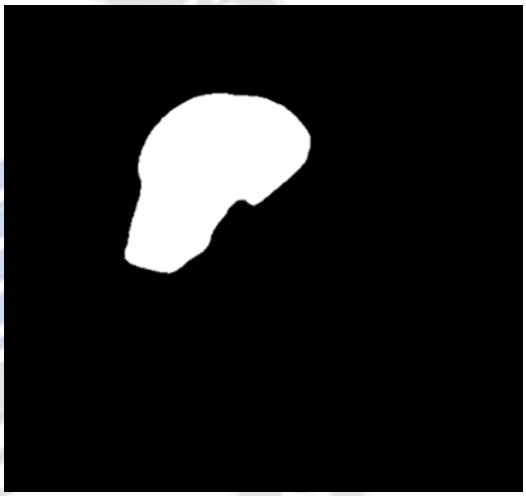

Figure: 10. Liver Segmentation

5. Conclusion

The Improved VGG19 (IVGG19) approach for segmenting and identifying liver cancer is presented in this work. To increase the precision of medical image identification, different layers of the neural network are used to extract features from the images. The feature-extraction procedure combines feature maps with a number of slices. The algorithm provided measurements of the liver volume that were 97.22% very accurate. The findings demonstrate that when data modifications, a better optimizer for feature updates, and appropriate class weights are used, the IVGG19 yields the best results. Keep in mind that testing was done using a restricted dataset and threefold cross-validation. The generated segmentation is then cleaned up to acquire the final results by removing the segmentation leaks. When it comes to diagnosing liver tumours, the proposed IVGGG19 technique provides great accuracy.

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