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# Hybrid Approach for the Detection of Liver Tumor using CNN and Rest net

Aman Sharma[1], Kiranpreet Kaur[2]
*Research scholar[1], Assistant professor[2] Computer Science Engineering Rayat Bahra University, Mohali, India*

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**ABSTRACT**
The segmentation of liver tumours from CT (Computed Tomography) images is a critical step in the diagnosis and treatment of liver cancer. However, it is difficult due to the variability of fuzzy boundaries, appearances, variable densities, forms, and sizes of lesions. In this article, a CNN (Convolutional Neural Network)-a based automatic technique for segmenting lesions from CT images is provided. CNNs are a type of DL (Deep Learning) model that extract hierarchical features from data using convolutional filters to. The liver is the body's biggest gland and a vital metabolic organ. Digestion, metabolism, and detoxification are all functions of the liver. Primary and secondary liver cancers are classified into 2 groups based on the cause of the malignancy. Primary liver cancer is a kind of cancer that develops in the liver's tissue. Hepatocellular carcinoma and Haemangioma are two kinds of primary liver cancer. In this article, the HFCNN (Hybridized Fully CNN) for liver tumour segmentation was suggested to detect liver cancer, which was theoretically and practically modelled to address the current issue of liver cancer. In the examination of liver cancer, HFCNN has been found to be a useful tool for semantic segmentation. This DL system reveals the concept of illuminating elements of a pre-trained deep neural network's decision-making process by analysing inner layers and defining aspects that result in predictions.

**Keywords:** Liver segmentation, liver cancer, Fully CNN, Neural Network, deep learning, RestNet50, VGG16.

## I. INTRODUCTION

The liver is the human body's biggest gland and the most significant metabolic organ. Digestion, metabolism, and detoxification are all functions of the liver. According to the cause of cancer, liver cancer is divided into 2 forms: primary & secondary liver cancer. Cancer that begins in the liver tissue is recognized as primary liver cancer. Hepatocellular carcinoma and Hemangioma are the two types of primary liver cancer. The most prevalent kind of liver cancer is HCC (Hepatocellular Carcinoma), which is the development of cancer cells in liver tissues.

Cancer is the 2nd largest cause of death worldwide. As per WHO (World Health Organization) figures, it was responsible for 8.8 million deaths in 2015, with 788,000 deaths due to liver cancer (WHO, 2020). The American Cancer Society estimates that in 2020, 42,710 new cases (30,186 in men and 12,638 in women) will be diagnosed, with 30,160 persons (10,140 women and 20,020 men) dying from intrahepatic bile duct cancer and primary liver cancer in the United States alone (ACS, 2020). With the use of multiple shallow and deep learning algorithms, various texture, shape, and gradient-based features have been extracted for the identification of liver cancer. For the liver cancer diagnosis in raw and non-pre-processed CT images, a computer-aided approach based on auto-covariance texture features is described. The irregularity of the liver texture image is captured using covariance-based features. The illumination changes, blur, poor contrast, orientation, and size of the liver picture were all common problems with the covariance-based technique.

Research in image processing is increasingly being conducted in the domain of deep learning. Several reports have demonstrated that CNNs can perform admirably on difficult tasks like visual picture categorization and object recognition [8, 9]. To segment cartilage in the knee, the CNNs model was utilized [10].

For example, deep CNNs, which were initially proposed by LeCun et al. [11], are multi-layered neural network-based supervised learning systems. In each intermediate layer, the abstraction is higher than the one before it. It can capture highly nonlinear input-output mappings. By mixing

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low and high-level properties, CNNs can extract hierarchical features.

## II. PROPOSED SYSTEM

- Detection and segmentation of liver cancer using an HFCNN.
- Designing a Hybrid model for classification and segmentation of liver tumours.
- The proposed HFCNN achieves high performance based on MRI images (dataset).

## III. DATASET AND PREPROCESSING

A dataset of 345 images has been taken and these images are CT images on which pre-processing was performed. By keeping unit variance, taking all CT images on the same scale. All images had different spacing ranging from 0.4mm to 2.6mm and for test images, all pixels were classified to detect the liver tumor or not with a class label 1 or 0. Image processing through the deep learning (FCNNs) RestNet50 model may be helpful in the early diagnosis of tumours rather than conventional approaches. For liver segmentation and assessment of the ROI ("Region of Interest"), the two Cascaded FCNNs have been employed in the majority of previous research.

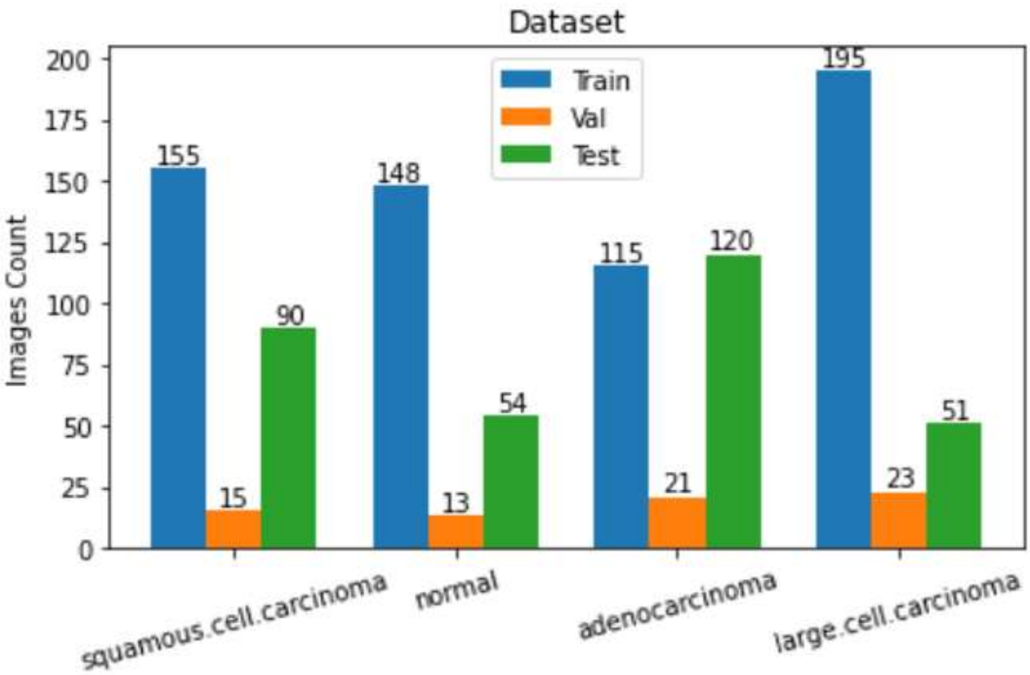


Fig: Dataset Description w.r.t Images Count Vs Liver disease types.

## IV. METHODOLOGY

The process is as follows:

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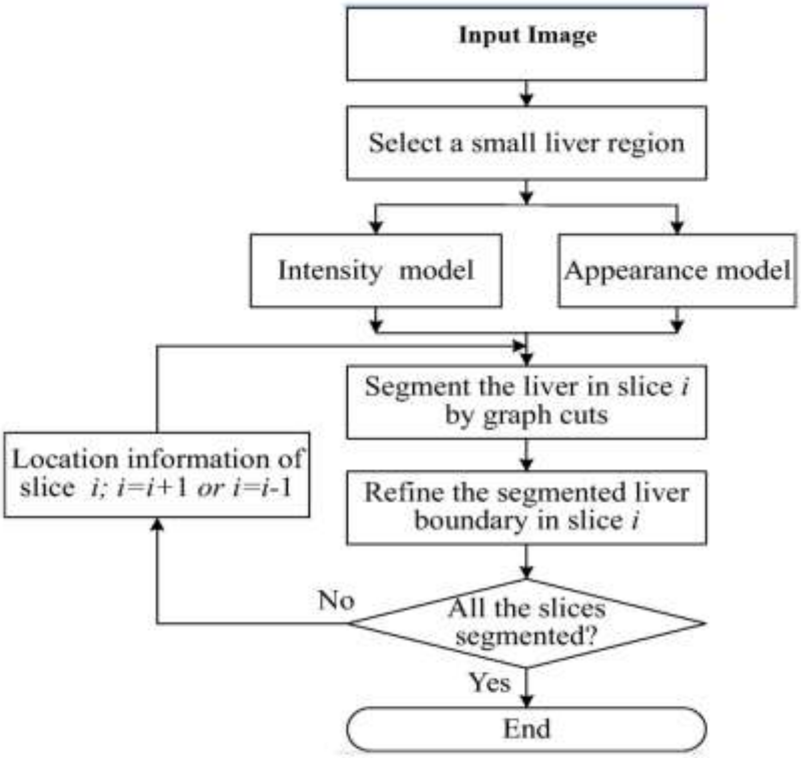


After collecting a sample from the liver tissue, imaging tests including CT, MRI (magnetic resonance imaging), and ultrasound may be utilized to identify the liver tumour. There is a high cost and a long time involved with this testing. Research on the viability of a new diagnostic method for chronic liver disease in individuals with risk factors. The implementation of a community-based non-invasive liver examination method is possible.

## V. PROPOSED ALGORITHM ARCHITECTURE IMPLEMENTATION

The eight convolutional layers, input layer, three dropout levels, four max-pooling layers, a Softmax layer, and two dense layers are all part of the suggested FULLY CNN architecture. The following are the stages in the CNN algorithm:

The system starts with a set of training images. The feature maps were recovered by running the data using 16 convolutional filters with a kernel size of five. A RELU activation function may be used to increase the weights. The key objective is to get the model to train faster.

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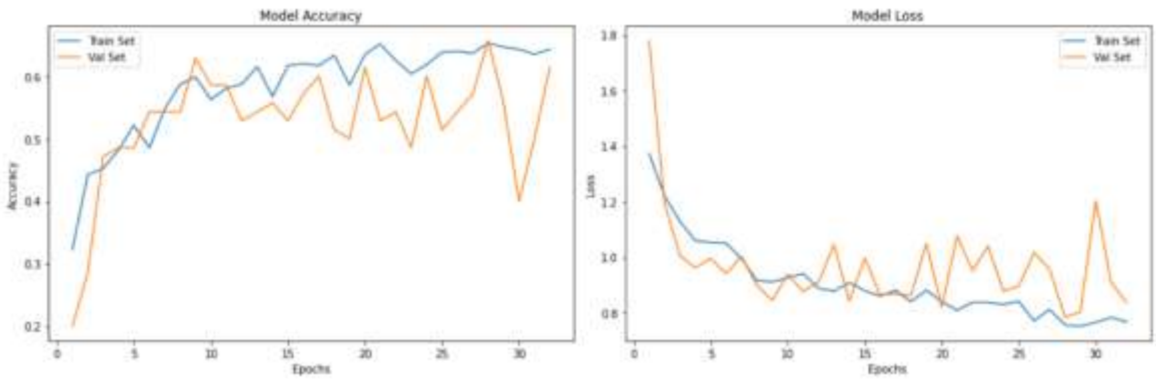
| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 348, 348, 32) | 896 |
| conv2d_1 (Conv2D) | (None, 346, 346, 32) | 9248 |
| max_pooling2d (MaxPooling2D) | (None, 173, 173, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 171, 171, 64) | 18496 |
| max_pooling2d_1 (MaxPooling2 | (None, 85, 85, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 83, 83, 128) | 73856 |
| max_pooling2d_2 (MaxPooling2 | (None, 41, 41, 128) | 0 |
| dropout (Dropout) | (None, 41, 41, 128) | 0 |
| flatten (Flatten) | (None, 215168) | 0 |
| dense (Dense) | (None, 64) | 13770816 |
| dropout_1 (Dropout) | (None, 64) | 0 |
| dense_1 (Dense) | (None, 4) | 260 |

Step 5: To utilize the max-pooling layer, use a max filter for down sampling the input vector with a 2×1 stride size. With fewer parameters and a better dropout layer, there is less overfitting, which decreases the need for further parameters.




## VI. EXPERIMENTS AND RESULTS

### 6.1 VGG-16 ALGORITHM

There are 41 layers in the network. A total of 16 layered weights may be learned: In all, there are thirteen convolutional layers and 3 fully connected layers in this system. The architecture of VGG-16, as described by Zisserman and Simonyan, is seen in Figure 2.

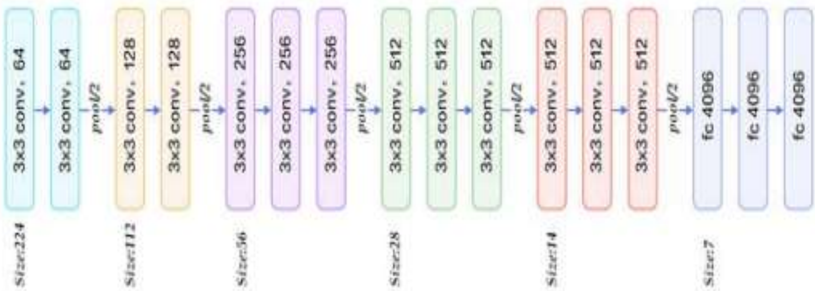



Figure: VGG16 Architecture

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Score and validation Dice Coefficient (F1-Score).

The epochs used to get the values are shown on the x-axis, while the accuracy is shown on the y-axis. The output to detect the liver disease using VGG16 is as follows:

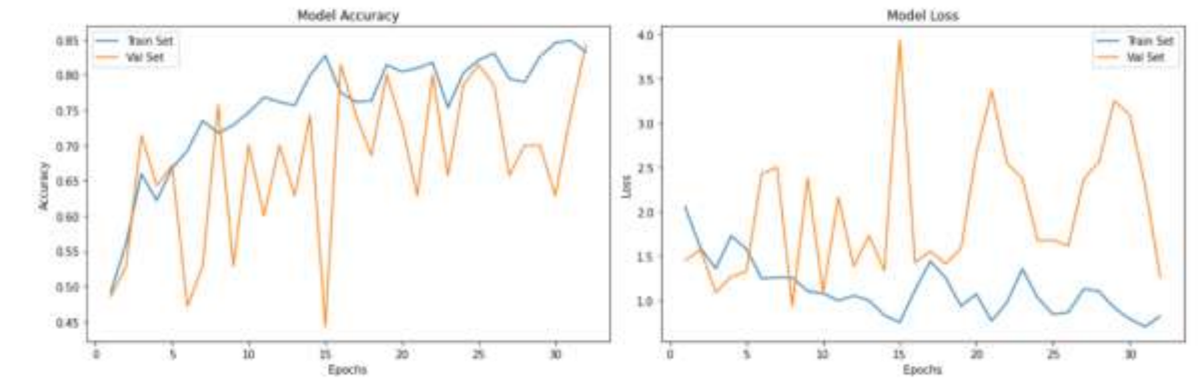
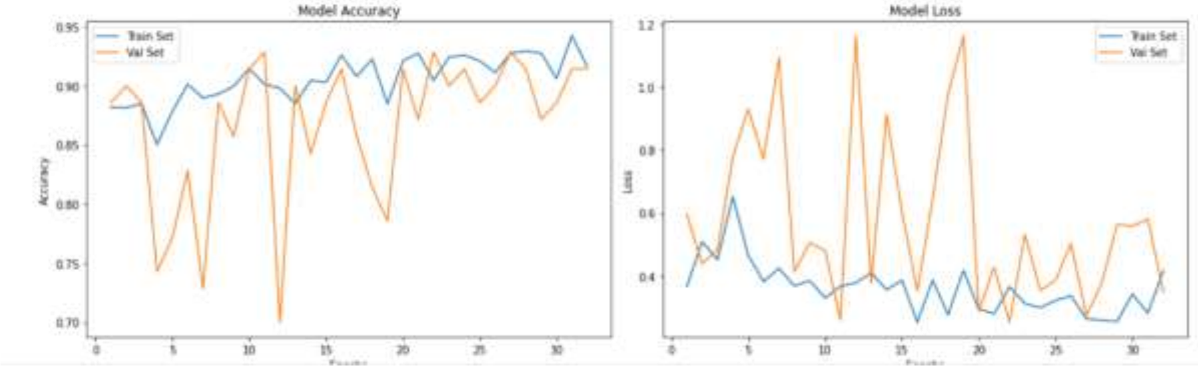



Fig: Results using VGG16

**6.2 RestNet5050**

As seen below, RestUNet had better outcomes to diagnose with efficiency and in a shorter time period:




Epochs Epochs

Fig: Result using RestNet5050

## VII. COMPARISION BETWEEN ALGORITHMS

Additional datasets and other pre-processing processes may improve the performance of the RestNet50 model. In the future, it has the potential to help in the diagnosis of small-scale liver cancers with an accuracy of 99.9%. The Validation of the Dice Coefficient (F1-Score) increased as well, suggesting that the experiment went well and that the model is suitable for application in detecting liver tumors. The fundamental benefit of the suggested procedure is that it does not need the removal of surrounding tissues or organs advance. Second, it can cope with a variety of liver shapes and intensities. Finally, there is no requirement for a previous model, which reduces the time and effort required for model generation and matching.

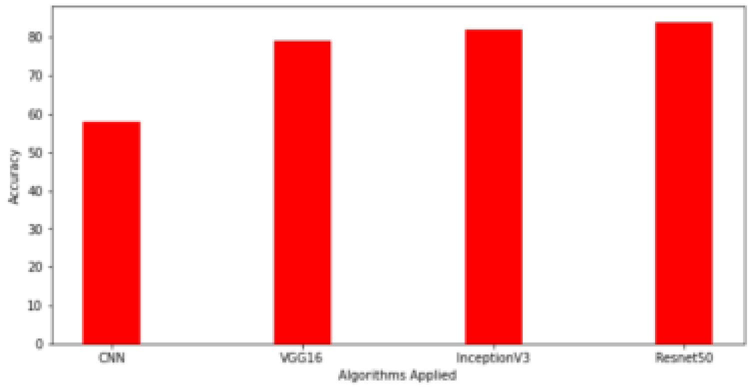



Fig: Comparison between Algorithms w. r .t Accuracy

## VIII. CONCLUSIONS

The findings revealed that CNNs aided in obtaining accuracy and that segmentation is the best strategy for diagnosing liver cancers. This method will be useful in the diagnosis of a variety of cancers. RestNet50 delivered excellent outcomes in terms of diagnosing quickly and efficiently. As can be seen from the above results, CNNs assisted us in achieving our goals and are possibly the ideal method to segment liver tumors. They should also be tried with malignancies other than liver tumors, as the ResNet showed promising results.

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