

# A Deep Learning Approach on Cirrhosis Diagnosis Utilizing Ultrasound B-Mode Images of Segmented Left Liver Lobes using Liver Biopsy as the Gold Standard

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### INTRODUCTION

Chronic Liver Disease (CLD) is currently one of the major causes of death worldwide [1]. Its end-stage cirrhosis leads to liver failure, complications such as portal hypertension with high probability of internal hemorrhage and high probability of developing hepatocellular carcinoma (HCC) [2]. The most preferred classification system for Fibrosis stage evaluation using liver biopsy (LB) is the Metavir scale consisting of five stages ranging from 0 to 4 (F0 = no fibrosis, F1 = mild fibrosis, F2 = significant fibrosis, F3 = severe fibrosis, F4 = cirrhosis) [3]. Liver Biopsy (LB) is considered the gold standard for estimation of CLD etiology and fibrosis stage but has serious limitations. It is invasive, expensive, and nearly 30% of patients suffer from postsurgical side effects [4]. Ultrasound (US) can be used to detect cirrhosis by visual inspection of liver surface irregularity, nodules and other qualitative criteria [5]. A Computer Aided Diagnosis System could further evaluate liver morphology and prove useful as a complementary tool to CLD diagnosis and severity.

# AIN

The aim of this study is to evaluate diagnostic performance of a deep learning scheme on detecting liver cirrhosis having as input US B-Mode images containing segmented left liver lobes delineated by an expert radiologist, on patients with CLD using LB as 'Gold Standard'.

# GoogLeNet Mean Accuracy:

- Training Data: 100%
- Validation Data: 91%

GoogLeNet Area Under the Curve (AUC) for both Classes (F0-F3 vs. F4):

• 0.992

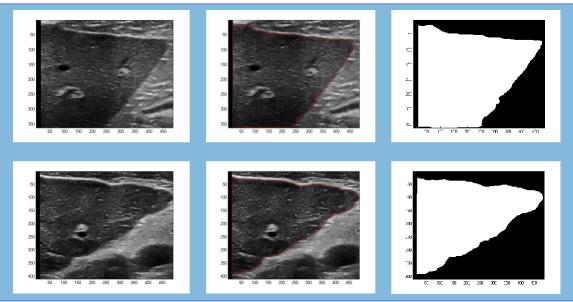
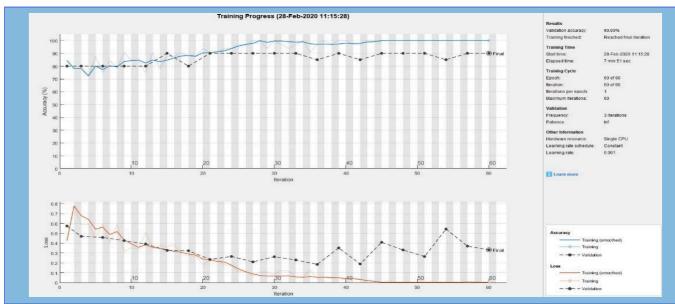


Figure 2. US B-Mode Liver Left Lobes (Left) and Liver Delineation (red color) by the radiologist (Middle) followed by the corresponding binary liver left lobe mask that is fed to GoogLeNet (Right). 1st Row: F0 fibrosis stage patient belonging to the Non-Cirrhotic Class. Liver surface has mild irregularity and liver lobe's edge is sharp. 2nd Row: F4 fibrosis stage patient belonging to the Cirrhotic Class. Liver surface has significant irregularity and liver lobe's edge is not sharp but circular.

# **RESULTS**



**Figure 3.** GoogLeNet Classification Results. Performance on Training Set is marked in aqua color, the corresponding loss is marked in red while performance and loss on Test Set are marked in black dotted line.

# **MATERIALS & METHODS**

#### **Clinical Data:**

- 69 consecutive CLD diagnosed patients (14 F0-F3 and 55 F4)

#### Examination:

 Standard US B-Mode Upper Abdomen Examination on Aixplorer US system by an Expert Radiologist and Liver Biopsy using the Metavir Scale (F0-F4) by an Expert Histopathologist

#### Image Acquisition:

 A B-Mode image containing left liver lobe was acquired and saved during the US examination.

#### Image Processing:

 The radiologist delineated the boundaries of liver surface for each patient on the saved image to acquire a binary image as liver's left lobe mask (pixels of liver left lobe having values of '1' and pixels out of the liver having values of '0')

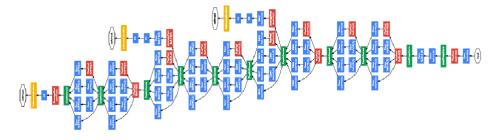


Figure 1. GoogLeNet Architecture (C. Szegedy et al. 2014, [6])

# **Deep Learning:**

- The cropped US images were given to GoogLeNet (Figure 2) a pre-trained deep learning network, using transfer learning.
- Data were separated in two classes according to their fibrosis Metavir stage: F0-F3 (Non-Cirrhotic Class) as class 1, and F4 (Cirrhotic Class) as class 2 and was randomly split in two parts, one for training (70%) and one for validation (30%).
- Since we have a small dataset (69 subjects) we repeated the data split/train/validation process 30 times to have a robust estimation of the network's performance.
- For each repetition the network's Training and Validation accuracy values were recorded.

# CONCLUSIONS

The results indicate that this scheme can be used as a supplementary tool for cirrhosis detection on regular US B-Mode abdomen examination.

While there is no insight on features that lead GoogLeNet to this result, the fact that only liver shape information was given is a strong indication that liver left lobe morphology contains valuable information for cirrhosis assessment.

More patients' data need be processed to further validate the proposed algorithm as a supplementary diagnostic tool for cirrhosis detection.

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