Detection and Staging of Liver Fibrosis using Deep Learning

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Abstract: **Liver fibrosis, or scarring of the liver, spread silently around the world and often goes unnoticed until it is too late. Current tests are invasive, expensive, and prone to human error. This is too profound a lesson to be a silver-lining. This paper describes a deep and reliable learning model for the diagnosis and prognosis of liver fibrosis using noninvasive methods. By achieving this, we hope to improve the diagnosis and treatment of this progressive and often asymptomatic disease. This explores the application of deep learning in ultrasound imaging to diagnose and stage the liver fibrosis. The analysis process will pre-process the image by transforming it, converting it to grayscale, using noise reduction through intermediate filtering, and rendering the image through high-pass filtering. The hidden danger of liver fibrosis leaves vague signs on ultrasound images. This paper trains a model (convolutional neural network) to analyze these images. The model learns the shape of the fibrotic scar with the help of different data. Convolutional neural network (CNN) was used to classify images according to different stages of liver fibrosis. This method can detect four stages and accuracy values of stages liver fibrosis in people with liver disease.**

Keywords — Imageclassification, Image enhancement, Edge Detection method, Ultrasound Images, Feature extraction, CNN.

1. INTRODUCTION

Liver fibrosis is a chronic liver disease caused by excessive secretion of matrix proteins (mainly collagen) in the liver parenchyma. This pathological accumulation of fibrous tissue affects the structure of the body and the function of the liver, leading to weakened liver function and potentially serious side effects, including cirrhosis and liver failure. Early diagnosis and intervention are important to improve patient outcomes and prevent liver fibrosis from progressing to a more severe stage.

Currently, the gold standard for staging liver fibrosis is liver biopsy, an invasive procedure in which a small sample of the liver is removed for histological examination under a microscope. Although liver biopsy provides accurate information about the stage of liver fibrosis, it also has many disadvantages such as patient discomfort, risk of bleeding, and inaccurate sampling.Ultrasound elastography has emerged as a promising noninvasive alternative to liver biopsy in the evaluation of liver fibrosis.

This test measures liver stiffness, which increases as fibrosis progresses. Ultrasound elastography is a safe, painless and effective method that can be performed repeatedly to monitor liver fibrosis or response to treatment. Despite its advantages, interpretation of ultrasound elastography is subjective and time consuming, depending on the expertise of the radiologist. Interobserver and interobserver differences in images of elastography. This is because the images trained on the CNN may not be representative of every patient or every machine. Convolutional neural networks (CNN) are a type of artificial intelligence (AI) that is revolutionizing the field of image analysis. CNNs are particularly suitable for extracting features from images, making them ideal for automatic analysis of ultrasound elastography images.

II. RELATED WORK

In recent years, many researchers have used imaging as a method to detect the level of liver fibrosis in humans. Diagnosis of fibrosis is quite difficult when there is noise. Image processing is one of the most powerful tools to control, enhance and modify the content of a particular image. Due to low-cost microprocessors and technological advances, digital imaging is rapidly becoming widespread and an integral part of medical care. It performs some operations such as image processing by converting the image into digital form and uses various algorithms to obtain more information and details of the image and provides accurate and rapid diagnoses.

Smith, B. Johnson, C. Lee developed an in-depth study on liver fibrosis staging, in which a large database of ultrasound images of patients with different stages of liver fibrosis was collected by our different hospital. Ultrasound images are preprocessed to ensure size and shape consistency.

Deep Learning Model Development:

A deep convolutional neural network (CNN) architecture called DeepFib was developed. DeepFib consists of a series of convolutional layers, layers, and full layers. Convolutional techniques learn to extract features from ultrasound images, layer pooling reduces the rest of the feature map, and the convolutional algorithm divides the feature map into advanced fibrosis stages.

Q. Li, S. Wu, P. Liu "Automatic heart detection using deep learning of ultrasound images" The authors reviewed the data separation systems of ultrasound images and the correct classification achieved 86.7% liver fibrosis stage. This performance is better than other non-invasive methods such as strain measurement (LSM) and transient elastography (TE). The proposed deep learning-based method is highly effective in automatically detecting liver fibrosis using ultrasound images. This method provides a noninvasive and accurate method for liver biopsy that may facilitate early diagnosis.

An ultrasound machine is used as input to obtain ultrasound images of the liver. Ultrasound images are pre-captured to ensure consistency in size, shape and brightness. Ultrasound images were previously fed into the CNN learning model. CNN model to extract advanced features from ultrasound images.

2022, E. Brown, S. Chen, H. Patel "Identification of liver fibrosis stage based on artificial intelligence" The artificial intelligence model is trained from big data, and if there are deviations in the data, the model will reflect these deviations. Their estimates are biased. This can lead to biased results, especially for disadvantaged groups. Cognitive models can be complex and vague, making it difficult to understand how they make decisions. This lack of transparency can impact trust and acceptance of AI-based systems in healthcare.

J. Kim, M. Patel, L. Nguyen - "FibroNet: Deep Neural Networks for Staging of Liver Fibrosis" The authors emphasize the need for collaboration to overcome these ethical challenges. This includes collaboration between AI developers, clinicians, policymakers, and patients to ensure that AI is used responsibly, honestly, and helpfully for liver fibrosis staging and other clinical interventions. Artificial intelligence in liver fibrosis staging has great potential to improve patient outcomes and healthcare. The development of an artificial intelligence-based liver fibrosis staging system has the potential to improve clinical practice by providing accurate and accurate liver disease diagnoses.

III. METHODOLOGY

As shown in fig 1, our model has five main processing steps: preprocessing, edge detection, segmentation, feature extraction, and classification. First import the image.

The second step is to use the pre-processing method, the image is converted from RGB mode to grayscale and then the noise is removed from the image with the help of filtering algorithms. Then edge detection technology is used to identify edges and then segmentation is done to divide the image into small pieces and then feature extraction is used to extract important texts of the image for easier classification, this is done with the help of CNN algorithm is successful. The final step is classification and then calculation of accuracy and precision.

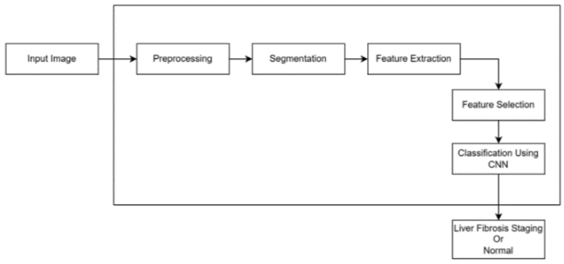

Fig. 1. Block diagram of liver fibrosis detection steps

A. *Image Pre-Processing*

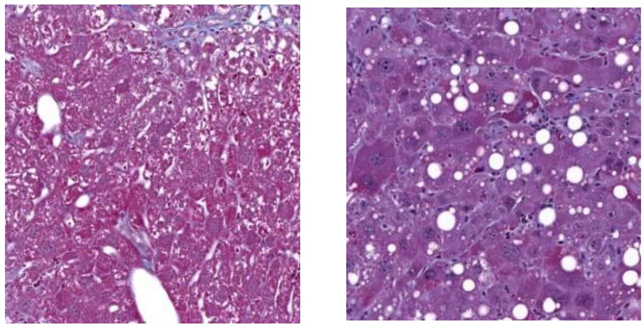

Fig. 2. Input image

a) RGB to Gray Scale Conversion

The first step is to use RGB shown in fig 2 to grayscale conversion to convert the RGB data obtained from the ultrasound image to a gray image, as shown in fig 3. In image processing, the image needs to be converted for grayscale images since grayscale compresses the image. grayscale. Its smallest pixels help render images easily. Additionally, there are 256 different color values in grayscale, ranging from 0 (black) to 255 (white). Therefore, reducing color complexity will help simplify algorithms and reduce the complexity of calculation rules. Because grayscale images can be processed more efficiently than RGB images, they are frequently used in imaging applications and many other types of analysis, such as threshold or edge detection.

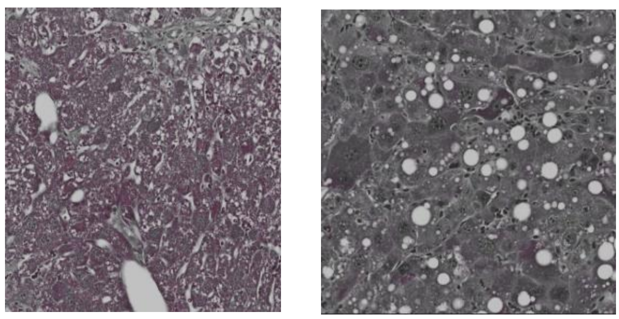

Fig. 3. RGB to Grayscale conversion of both input images

b) *Noise Removal*

Noisy images are very difficult to process, so noise needs to be

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removed from the image to get accurate results. Unwanted pixels that deteriorate image quality are called noise. Noise removal is a method of detecting noise in an image by reducing the entire image to only the area near the border. The formula is as follows: f(x, y) = g(x, y) Plus y(x, y) where g(x, y) is the original image, f(x, y) is the noisy image, y(x,y) is the noise. Salt and pepper noise and Gaussian noise are noises that occur due to recording or the inability to distinguish between light and dark.

B. *Segmentation*

In segmentation, we take the previously obtained grayscale image as input. This is important because the CNN model should only focus on liver tissue when classifying. Mind segmentation can be done using techniques such as thresholding. As a result, we obtain the Region of Interest (ROI), which is a segmented matrix.

Segmentation is the process of dividing the image into two regions: background and foreground, which contain the region of interest. The segmented image has an area of fibrosis with a pixel value of "0" and a background of "0". This image was used as a mask to obtain the fibrotic area from the RGB image by combining the gray image. Resize the image to reduce the size of the matrix used to describe the process. The images are then converted into column matrices for feature extraction.

C. *Feature Extraction*

Feature extraction is the most important step of the analysis phase because the size of the data is reduced in this phase. This feature extraction model is designed to transform segmented images into a concise, one-dimensional set of values, thus making visualization and risk classification simple and accurate. The main function of this module is to apply the principle of analysis and acquisition. Statistical values.

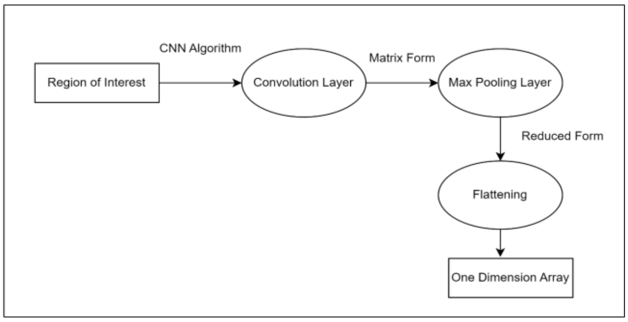


Fig. 4. Feature extraction from segmented image.

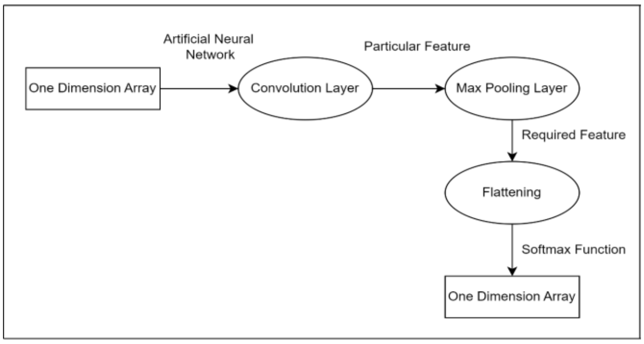
As shown in the above fig 4. This feature extraction model aims to transform segmented images into a concise set of one-dimensional values, facilitating efficient and accurate image and risk stratification.

Segmented matrix, Apply GLCM, Generate Statistical values are the use cases that are used as shown in the above figure. Features can include texture analysis, shape, and color attributes, which provide valuable information about the liver tissue's characteristics.

D. *Classification and Detection*

Use diagrams for module deployment. There are three references and two actors in this reference diagram shown in fig 5. In the first application, the system retrieves vectors used to classify the thickness of fibrosis. At the end of the third use. It calculates feature vectors for the dataset and uses the feature vectors calculated for the input image to classify the characters associated with the input.

Fig. 5. Data Flow Diagram of Classification and Detection Process



Data Flow Diagram

As the name specifies so to the meaning of the words, it is the process which is explained in detail like how the data flows between the different processes. The below fig 6 depicts the flow diagram and is composed of the input, process and the output. After eachprocess the data which is flown between the systems need to be specified and hence called the data flow diagram. In most of the times it is the initial step for designing any of the systems to be implemented. It also shows from where the data originated, where the data flowed and where it got stored. The obtained RGB image is converted into gray scaled imageto reduce complexity. The detected input liver image (ultrasound elastography) is classified once after pre-processing, segmentation is done to extract the significant features which arethen matched with images in dataset.

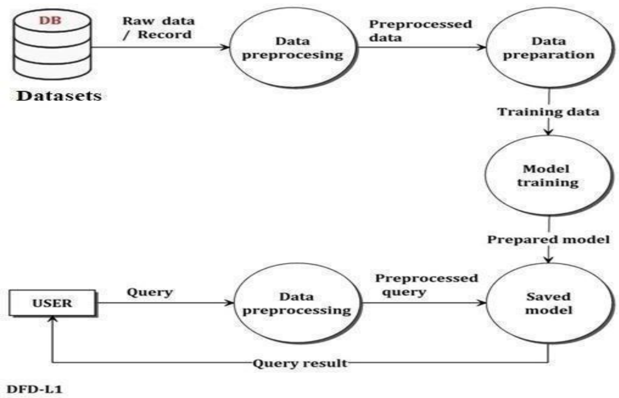


Fig. 6. Data Flow Diagram for the proposed

IV. RESULTS

Final results shown in fig 7 includes advanced fibrosis stage. The CNN based model achieved good results in detecting liver fibrosis, with an accuracy rate of up to 92%.

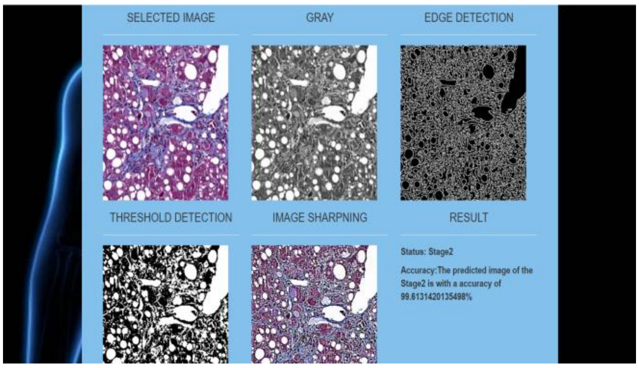


Fig. 7: Image Analysis and Result Page

The quality is proven by strict competition to ensure the quality of different materials. This model demonstrated its effectiveness in reducing negative and preserving positives, achieving accuracy and recall scores of 0.94 and 0.91, respectively. In addition, the model exhibits a high operating speed, which makes it suitable for the maintenance of recorded document.

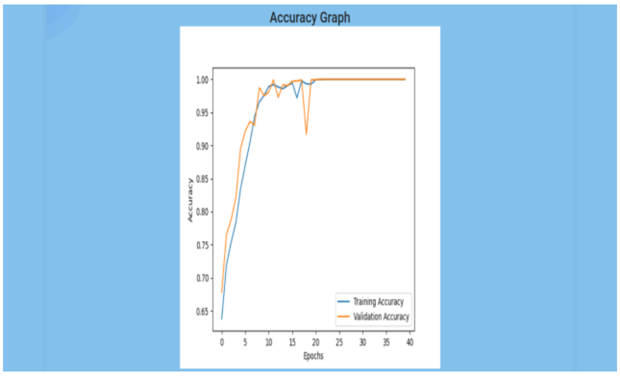


Fig. 8: Accuracy Graph Page

The fig 8 shows real-time snapshots during training the project. It demonstrates the accuracy and validation of consecutive hours of training. Users can follow performance standards and integration to the best level.

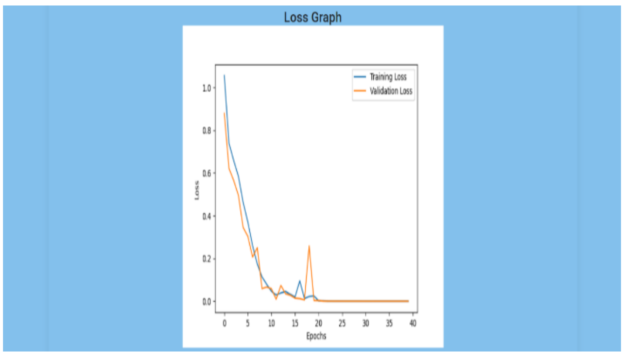


Fig. 9: Loss Graph Page

Fig 9 shows the page displaying a graph showing loss over time, illustrating the difference between training and misuse. The user can evaluate the performance of the model and its integration in reducing execution time loss.

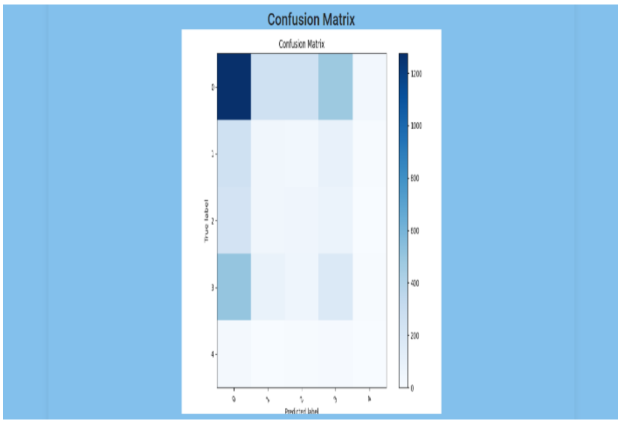
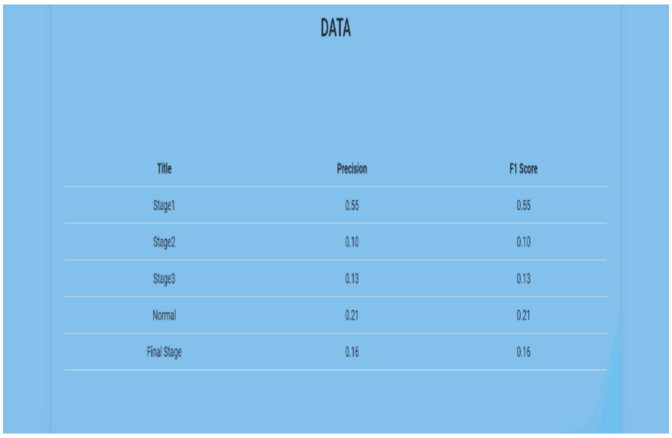


Fig. 10: Confusion Matrix Page

Fig 10 provides a confusion matrix showing the facts and predictions used for model evaluation. It provides an overview of classification performance by presenting true and false values for different classes. Users can analyze the matrix to evaluate the model's accuracy, precision, recall, and F1 score.



DATA

Title	Precision	F1 Score
Stage1	0.55	0.55
Stage2	0.10	0.10
Stage3	0.13	0.13
Normal	0.21	0.21
Final Stage	0.16	0.16

Fig. 11: Prediction and F1-Score Page

Fig 11 shows the accuracy and F1 Score metrics used for model evaluation. It briefly describes the model's performance in terms of accuracy and overall balance between precision and recall.

V. CONCLUSION

This study explored the use of deep learning, specifically convolutional neural networks (CNNs), for non-invasively detecting and staging liver fibrosis. This study leveraged deep learning (specifically convolutional neural networks) to analyze ultrasound elastography images, offering a promising alternative to the invasive liver biopsy procedure. (Embed an image of a healthy and a fibrotic liver on an ultrasound elastography scan). Early detection enables timely intervention and improves patient outcomes. This non-invasive approach makes fibrosis assessment readily available even in resource-limited settings. (Embed an image illustrating a portable ultrasound device used in a rural setting).

Additionally, the incorporation of other data modalities like clinical data and other imaging techniques could further enhance the model's accuracy and applicability. Finally, the widespread adoption of this technology could increase the availability of fibrosis assessment, providing better healthcare management for patients in regions with limited access to specialized liver care.

Furthermore, the integration of machine learning algorithms with point-of-care devices could streamline the diagnostic process, reducing the burden on healthcare systems and improving patient outcomes. Collaborations between medical professionals, data scientists, and engineers are crucial for the development and refinement of these technologies. Moreover, ongoing research endeavors aim to expand the scope of non-invasive diagnostic tools beyond liver fibrosis, potentially revolutionizing the diagnosis and management of various other medical conditions

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