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COMPUTERIZED IDENTIFICATION OF THE PHASES OF LIVER FIBROSIS BY ULTRASONOGRAPHY: QUANTITATIVE STUDY OF DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract

This study aimed to evaluate the effectiveness of a widely used and well-respected deep convolutional neural network and to determine the computerized detection of liver fibrosis episodes using ultrasonography. In three months of 2024, a quantitative study was conducted in several settings in Bangladesh. The design of the study was quantitative; therefore informed consent was not required. While non-invasive techniques like transient elastography are frequently employed to assess liver fibrosis, mistakes may arise in situations involving a constricted liver or ascites. In this work, we used US photos to fine-tune the model following transfer learning on ImageNet. In this study, the learning-rate scheduler and optimization algorithm was Adam optimizer, respectively, while the loss function used for training the models was CrossEntropyLoss. Accuracy, sensitivity, specificity, and positive and negative likelihood ratios were used to assess DCNN performance. Furthermore, the effectiveness of DCNNs was evaluated using the area under the receiver operating characteristic curve (AUC) with a 95% confidential interval for five-level categorization. 49 were the median age (IQR: 42–58). F0 is generally easy to get, and 33.2% of the dataset consists of such data. 33.2% of the dataset was made up of liver fibrosis stage 4, or F4. However, because so few individuals were evaluated in the early stages of hepatic fibrosis, the proportions of F1 (13.2%), F2 (8.4%), and F3 (24.2%) were quite low. Using a computer vision method, a data augmentation of the images expands the size of a limited dataset. In the final analysis, researchers have shown that DCNNs can accurately classify METAVIR grade employing traditional US pictures. The DCNNs-based diagnosis of liver fibrosis using B-mode images will be an effective instrument for promoting radiologists in the clinical setting, as US imaging is a commonly accessible method and is primarily

employed in periodic subsequent studies of patients with persistent liver disease. Additional enhancement and verification might be necessary, though.

Keywords: computerized identification, phases, liver fibrosis, ultrasonography, deep convolutional neural network

INTRODUCTION

The liver, which accounts for 2% of the body's mass and weighs close to 1.5 kg, is a vital organ. The liver carries out important tasks that keep life alive. Hepatocytes and hepatic sinusoids play different biological functions in the liver. The body's biochemical factory is referred to as the liver [1]. A WHO research states that liver illnesses account for 62.6% of deaths, with cirrhosis accounting for 54.3% of these cases; this region accounts for more than two-thirds of global cases of acute hepatitis [2]. A WHO report [3] states that the most common cause of liver disease-related death in the Asian region is cirrhosis. Hepatocellular carcinoma, cirrhosis, and hepatitis C are just a few of the liver illnesses that claimed the lives of over 399,000 individuals in 2016. A plan to designate liver disease as a public health issue has been developed by the WHO. The past few decades have demonstrated that anomalies such as liver abscesses can occasionally be rather serious and are influenced by significant changes in epidemiology and risk factors [4]. Blood infections, stomach infections, wound infections, and bacterial or parasite infections are the most frequent causes of liver abscesses. It's critical to understand the severity, diagnosis, and course of therapy for abscesses to prevent problems in patients who remain untreated. Biliary tract disorders are important sources of pyogenic liver abscesses [5]. The liver is harmed by hypoxia, ischemia, drug exposure, and infection. However, after a certain point, injured cells cannot heal, resulting in irreversible harm. This can occasionally result in fibrosis, or non-functioning cells or scar tissue, in the liver [6]. Liver fibrosis is the outcome of damage to the hepatocytes produced by a variety of etiologies, including infection, non-alcoholic fatty liver, alcohol, hereditary metabolic disease, immunological disease, and medication usage [7]. These factors also activate the hepatic stellate cell and promote cytokine release and collagen deposition.

The most advanced and irreparable stage of liver fibrosis is cirrhosis, which can lead to hepatocellular cancer and portal hypertension [8]. Since the severity of liver fibrosis affects the prognosis and management of chronic liver illnesses, early and correct identification of liver fibrosis is crucial in clinical practice. The most accurate method for diagnosing and grading liver fibrosis is the histological evaluation performed via liver biopsy. However, because liver parenchyma specimens are tiny, liver biopsy is susceptible to sampling errors as well as intra- and inter-observer differences [9, 10]. It is also invasive, which increases the risk of several consequences, including possibly fatal ones. It is not advised to do recurrent liver biopsies to track the course of the disease. To get around these restrictions, non-invasive techniques including magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound (US) imaging have been researched and, while they need more time and equipment, have produced encouraging findings for assessing liver fibrosis [11–13]. In addition to providing morphological information (such as parenchymal alterations and portal hypertension), these imaging modalities also provide functional information (such as tissue stiffness) that is associated with the stage of fibrosis. The most extensively used and radiation-free modality among them is US imaging. Therefore, to detect hepatocellular carcinoma and assess the degree of liver fibrosis in patients with chronic hepatitis or liver cirrhosis, US imaging is the most commonly used modality for routine follow-up. According to reports, surface nodularity and parenchymal echogenicity—which are categorized as fine, slightly medium, and moderately coarse—change as fibrosis advances [14]. Using MR and CT images, several recent research have demonstrated that deep convolutional neural networks (DCNNs) based diagnosis and assessment of liver fibrosis is a workable option [15–20]. Using US B-mode pictures, a DCNN-based quaternary classification model was created to categorize liver cirrhosis (F0/F1/F23/F4) [21]. To classify chronic liver disease in renal US imaging, the efficacy of

ResNet pre-trained with the ImageNet dataset was assessed [22]. TNet and BNet, which were constructed using pre-trained VGG-19, were able to achieve classification accuracies of 86.3% and 86.5%, respectively, for classifying thyroid nodules and breast lesions in US images [23]. To identify thyroid nodules, a deep learning architecture comprising a feature extraction network, an attention-based feature aggregation network, and a classification network was also suggested [24]. The approach used VGGNet for transfer learning, and the METAVIR score classification accuracy was 83.5%. When applying US photos obtained from another domain, the model trained from images obtained from a restricted domain could be biased toward the feature of the corresponding machine and perform poorly. Multi-domain data are required to represent actual clinical scenarios because there are numerous varieties of US equipment. This study aimed to evaluate the effectiveness of a widely used and well-respected deep convolutional neural network and to determine the computerized detection of liver fibrosis episodes using ultrasonography.

MATERIALS AND METHODS

In three months of 2024, a quantitative study was conducted in several settings in Bangladesh, including the World Trade Center Chittagong, Port City International University Chittagong, Bangladesh; Grameen Caledonian College of Nursing, Bangladesh; and Upazila Health & Family Planning officer, Damudya, Shariatpur, Bangladesh. The institutional review boards of each investigation location gave their approval to this project. The design of the study was quantitative; therefore informed consent was not required. While non-invasive techniques like transient elastography are frequently employed to assess liver fibrosis, mistakes may arise in situations involving a constricted liver or ascites. Among them, this study included individuals who had a liver US performed no more than two months before a biopsy or surgery. Regardless of the scanning plane, a radiologist with fifteen years of abdominal US experience examined every image and chose liver scans. Every image is captured with a convex probe. Based on the pathology outcomes of the biopsy or hepatectomy, we classified liver fibrosis in this study for the automated diagnosis of liver fibrosis. Keep in mind that a pathology report is a medical record that offers a definitive diagnosis derived from a tissue specimen's microscopic examination. Five classes make up the METAVIR score: F0, F1, F2, F3, and F4. The codes F0, F1, F2, and F4 represent different stages of the disease: F0 represents no fibrosis; F1, portal fibrosis with few septa and abnormalities in a smaller aberrant area; F3, multiple septa without cirrhosis and noticeable abnormalities; and F4, cirrhosis. We tried classifying liver fibrosis into five categories: F0, F1, F2, F3, and F4. Throughout the dataset, training and validation data were used in an 8:2 ratio. The dataset's distribution ratio needs to be taken into account before training a model. Particularly, there is an inconsistency in the degree of data concerning diseases that are hard to identify in their early stages, like liver fibrosis. Since the US images created with a convex array have a fan shape, horizontal flips were solely used in this work to augment the data. For model training, the resulting photos were scaled and normalized to a pixel resolution of 224×224. The input images' sizes need to be suitably altered to match the proportions that the DCNN models support. 224×224 is the authorized input size for the main models that we employed in our experiments. With a fraction of the computational effort, this innovative method achieves performance that is either equivalent to or better than classic convolutional models by successfully capturing global dependencies. As a fully connected layer, the final classifier g is used to create a linear classifier. The softmax function is used to normalize the output value of g to a probability. To optimize the probability of the target class, the objective cross-entropy function is specified. Ultimately, the objective function is optimized by the training of the parameter θ. A model trained on a sizable dataset from a different domain is used in transfer learning. The 1000 classes in the ImageNet dataset are typically utilized for pre-training. Extensive datasets are useful for model training to extract relevant features from input photos. The convolution filter of the pre-trained model is more optimal than scratch learning when learning a new domain from the pre-training since it has already been taught to discover high-level features. Even when the convolution layers are frozen, the models can produce reliable results

if the pre-trained and post-trained datasets belong to related domains. However, because ImageNet and medical images contain distinct cardinal characteristics, the model needs to be retrained depending on the overall parameters when post-training using medical images. In this work, we used US photos to fine-tune the model following transfer learning on ImageNet [25]. In this study, the learning-rate scheduler and optimization algorithm were CosineAnnealingLR and Adam optimizer, respectively, while the loss function used for training the models was CrossEntropyLoss by Negative Loglikelihood. The scheduler set the initial learning rate to 0.0001 and changed it every 50 epochs to a number that was almost zero. Using a 64-batch size, we trained the model for 1000 epochs. Accuracy, sensitivity, specificity, and positive and negative likelihood ratios were used to assess DCNN performance. Furthermore, the effectiveness of DCNNs was evaluated using the area under the receiver operating characteristic curve (AUC) with a 95% confidential interval for five-level (F0/F1/F2/F3/F4) categorization.

RESULTS AND DISCUSSION

The medical conditions of the 190 individuals (129 of them were male) that were a part of this investigation are collected in Table 1. 49 were the median age (IQR: 42–58). US equipment provided a summary of the patient and imaging counts utilized in this investigation. Table 1 displays the ranking of liver fibrosis grades. F0 is generally easy to get, and 33.2% of the dataset consists of such data. 33.2% of the dataset was made up of liver fibrosis stage 4, or F4. However, because so few individuals were evaluated in the early stages of hepatic fibrosis, the proportions of F1 (13.2%), F2 (8.4%), and F3 (24.2%) were quite low. A model's training may be skewed and overfit due to this data imbalance [25].

Table 1: Baseline Patients Characteristics

Variables	Values
Number of images (n)	190
Sex (M:F)	129: 61
Age (years)	49 (42–58)
Total bilirubin (mg/dL)	0.86 (0.61–1.49)
AST (U/L)	45 (25-94)
ALT (U/L)	40 (21–88)
Albumin (g/dL)	4.1 (3.5–4.4)
Platelet count (10^3/L)	164 (112–243)
Prothrombin time (INR)	1.08 (1.02–1.18)
METAVIR score	
F0	65 (33.2%)
F1	25 (13.2%)
F2	16 (8.4%)
F3	46 (24.2%)
F4	38 (20%)

Using a computer vision method, a data augmentation of the images expands the size of a limited dataset. In general, flipping, color jitter, cropping, rotation, translation, and noise generation are used for such augmentation [26]. We applied transfer learning for model training (Fig. 1) because scratch learning is valid when the number of training data is more than 5000 per class [27, 28]. Table 2 summarizes the diagnostic performance of deep convolutional neural networks for five-level classification. Similar values were achieved for five models (Fig. 2).

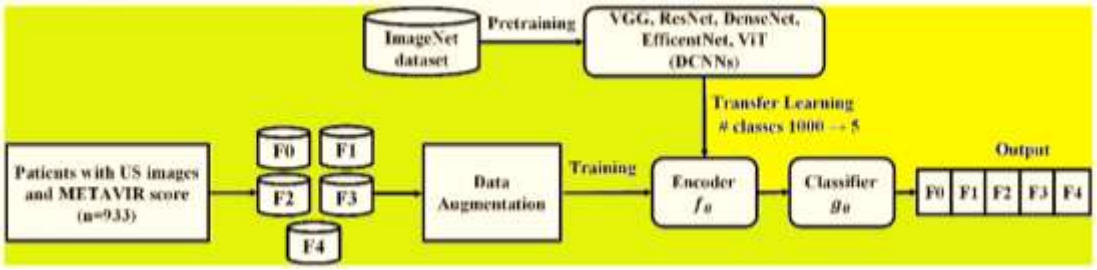

Figure 1: Training diagram of deep convolutional neural network

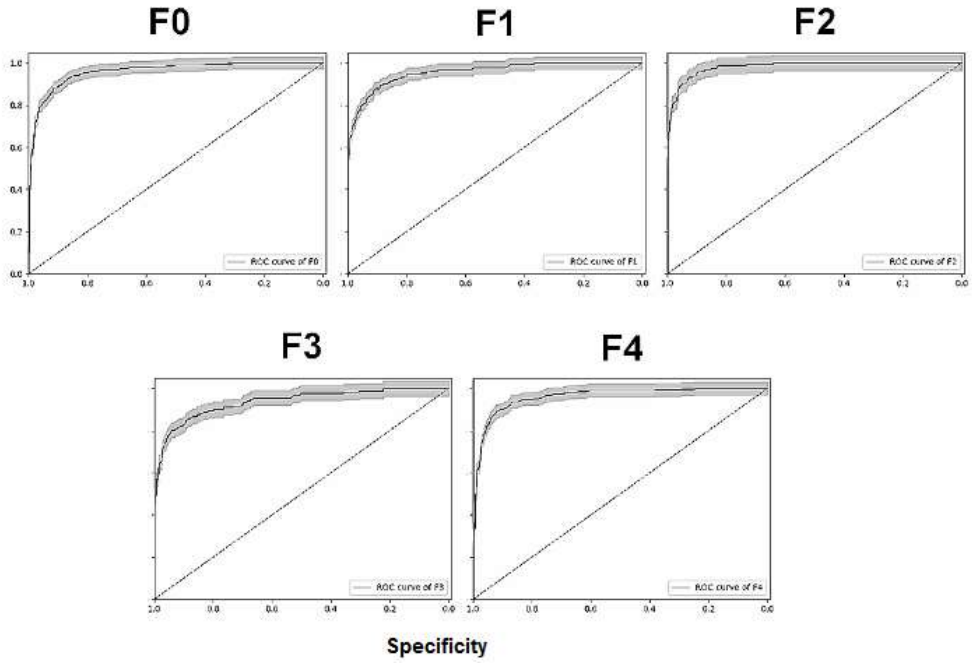

Figure 2: Automated classification of liver fibrosis stages using ultrasound imaging

Table 2: Diagnostic Performance of DCNNs for Five Level Classifications

Model	Staging	AUC	Accuracy	Sensitivity	Specificity
DCNNs	F0	0.96	0.91	0.89	0.92
	F1	0.96	0.94	0.72	0.98
	F2	0.98	0.96	0.86	0.98
	F3	0.94	0.93	0.74	0.97
	F4	0.96	0.92	0.87	0.94

***AUC = receiver operating characteristic curve; DCNNs = Deep Convolutional Neural Networks**

In this work, we show that DCNNs formed via transfer learning on ImageNet can accurately (AUC: > 0.95, reliability: 0.94) diagnose the various stages of liver fibrosis based on the METAVIR score using conventional B-mode images from multiple US machines, comparatively reduced computational complexity—achieving the best results. Using US pictures, several studies on DCNN-based automatic detection and classification have been carried out recently [29]. Research was also conducted on the automated staging of liver fibrosis using US images [14]. While the categorization for substantial fibrosis (F2 or greater) achieved high performance (AUC: 0.90, accuracy: 0.94), the precision for quadrilateral categorization (F0/F1/F23/F4) was relatively low (0.83). The instructional information asymmetry is the primary cause of this. To reduce prejudice and overfitting of the model during training, we augmented the data in our method. Furthermore, our findings demonstrated that improved performance is not always a guarantee of computationally complicated networks. Since it can decrease computational complexity as well as training time, using DCNNs with fewer calculations has some benefits. This will make it possible to quickly and simply apply DCNNs for automated categorization on standard US machines. When assessing the liver in patients with chronic liver disease, the US is frequently employed. Even with routine follow-up, it might be challenging to forecast the stage of liver fibrosis only from US B-mode pictures because the liver's morphology and echogenicity do not significantly alter in the early stages of the disease. As a result, US elastography has been employed as a potential imaging method to assess liver fibrosis and the elastic modulus of tissues [30–34]. However, because it is still challenging to distinguish the five stages of liver fibrosis even using elastography, liver fibrosis stage was separated into two categories in the majority of research, such as F4 versus others. Our

method, when installed on current equipment, will provide a practical substitute for evaluating liver fibrosis without requiring the choice of an imaging surface or extra tools for add-on tests like elastography and Fibroscan, particularly in low- to middle-income nations. We compared the outcomes of the primary backbone models—which ranged from shallow to deep networks—in this work. Consequently, it is reasonable for evaluating the performance using the basic forms that make up the framework, including the most recent baseline like Vit, for an objective assessment of DCNN's effectiveness. There are various restrictions on our investigation. First, it might impair network performance because we employed information enhancement to equalize the dataset for every stage. For our method to be utilized in practice, the model needs to be calibrated with an adequate dataset without adding additional data. Second, the US pictures used for training were acquired by well-trained radiologists. Since the US relies heavily on its radiologists, photos taken by inexperienced radiologists might have to be provided for low- to middle-income nations with poorly functioning healthcare systems. Third, in order to reduce computational load, we scaled the photos to 224 × 224 for the training process. As a result, our method may be able to recognize liver fibrosis using general morphological parameters like liver surface irregularity.

CONCLUSION

Computerized classification for fibrosis of the liver might alleviate the lack of proficient radiologists, particularly in low-to-middle-income nations. Ultrasound detection is the most commonly done procedure for patients with chronic hepatitis or liver cirrhosis. However, ultrasonography is significant and the assessment of ultrasonography visuals is interpretive, consequently, competent radiologists are needed for assessment. In the final analysis, researchers have shown that DCNNs can accurately classify METAVIR grade employing traditional US pictures. The DCNNs-based diagnosis of liver fibrosis using B-mode images will be an effective instrument for promoting radiologists in the clinical setting, as US imaging is a commonly accessible method and is primarily employed in periodic subsequent studies of patients with persistent liver disease. Additional enhancement and verification might be necessary, though.

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