

Deep Learning Based Hybrid Classifier for Analyzing Hepatitis C in Ultrasound Images

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ABSTRACT: Although liver biopsy is the gold standard for identifying diffuse liver disorders, it is an intrusive procedure with a host of negative side effects. Physician subjectivity may affect the ultrasonography diagnosis of diffuse liver disease. As a result, there is still a clear need for an appropriate classification of liver illnesses. In this article, an unique deep classifier made up of deep convolutional neural networks (CNNs) that have already been trained is proposed to categories the liver condition. The variants of ResNet and AlexNet are a few networks that are combined with fully connected networks (FCNs). Transfer learning can be used to extract deep features that can offer adequate categorization data. Then, an FCN can depict images of the disease in its many stages, including tissue, liver hepatitis, and hepatitis. To discriminate between these liver images, three different (normal/cirrhosis, perfectly natural, and cirrhosis/hepatitis) and 3 (normal/cirrhosis/hepatitis) models were trained. A hybrid classifier is presented in order to integrate the graded odds of the classes produced by each individual classifier since two-class classifiers performed better than three-class classifiers. The class with the highest score is then chosen using a majority voting technique. The experimental results demonstrate an high accuracy when liver images were divided into three classes using ResNet50 and a hybrid classifier.

Keywords: Classifier for Hepatitis C using Hybrid Models, Deep Learning, Hepatitis C



1. INTRODUCTION

On a worldwide basis, it has been noted that there are more fatalities from liver disease than from other serious illnesses. This is due to the fact that the most common types of jaundice do not first manifest any symptoms. Therefore, a precise prospective diagnosis for each patient is essential to creating the most personalized treatment strategy.

Cirrhosis is a disorder that worsens with time and cannot be reversed. It increases the risk of liver cancer and hepatocellular carcinoma by encouraging the growth of scar tissue in the liver (HCC). The most typical kind of primary liver cancer is HCC. Individuals who have long-term liver disorders, such as cirrhosis brought on by hepatitis B or C infection, are more likely to develop hepatocellular carcinoma [1].

2. CONTRIBUTION

- On this study, a computational technique for automatically classifying diffuse liver disorders in ultrasound images is investigated
- Hepatitis, cirrhosis, and normal ultrasound liver images were distinguished using deep learning approaches.

- Classifiers for two and three classes were trained using a variety of networks, including ResNeXt, ResNets, and AlexNet.
- To increase the three-class classification's accuracy, a hybrid classifier was suggested.

3. RESEARCH ASPECTS

As a standard procedure, liver biopsy can occasionally be advised to evaluate the liver status and assist doctors in determining the best course of therapy for patients. But in addition to being extremely costly and unpopular with patients, it is also seen to be a risky and intrusive operation [2]. Therefore, the availability of a continuous noninvasive monitoring technique, especially during the initial stages of liver disease, can save many individuals and lower their overall treatment costs.

In comparison to other imaging modalities, ultrasound offers an affordable, secure, and non-invasive imaging technique [3]. It also offers mobility and real-time capabilities. It is a global strategy that has been widely used for years in clinical settings to diagnose or engage with the treatment procedure of the illnesses among those individuals who specifically suffer from a chronic liver disease [4]. This is due to recent advancements in digital technology.

Despite the advantages already indicated, there are several limitations to ultrasound-based imaging that must be overlooked. First off, the subsequent interpretation and evaluation of the data may be influenced by the doctor's expertise with and understanding of the ultrasonography. Particularly, even a qualified person could find it challenging to visually analyse data in obese people. Second, further research is needed to compare the diagnostic capabilities of ultrasound-based imaging techniques to those of other imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), and elastography [4].

Computer-aided diagnosis and intelligent approaches were developed to assist doctors and radiologists in making more precise and objective diagnoses in response to these difficulties.

4. KEY STUDIES AND RELATED WORK

Key studies examining the diagnostic accuracy of ultrasound imaging for liver illness are as follows: Wavelet transform of B-scan liver images were used by Mojsilovi et al. [5] to define diffuse disorders. Using a combination of imaging characteristics, Ogawac et al. [6] were able to determine the liver's health. Yeh et al. [7] used the support vector machine (SVM) method to classify the severity of liver fibrosis based on ultrasound images acquired in the B-mode. To distinguish between healthy liver, hepatitis, and cirrhosis, Wu Chun Ming et al. [8] used textural characteristics and a Bayes classifier, resulting in a 90.00% accuracy rate. In order to recognise ultrasound images for cirrhosis, Lei et al. [9] used the dictionary learning techniques of Local Binary Pattern (LBP), Gabor transform, and K-SVD. Classification accuracies of 93.33%, 90.00%, and 89.67% were achieved by Chen Fei et al. [10] when they retrieved statistical and fractal characteristics for normal liver, cirrhosis, and hepatoma identification. With a sensitivity of 96.00% and a specificity of 94.00%, K. Mala et al. [11] retrieved multi-resolution statistical texture characteristics using Probabilistic Neural Network (PNN) to differentiate cirrhosis from fatty liver in CT images. Our colleagues [12] proposed a scheme to classify ultrasound images of diffuse liver diseases into normal, cirrhosis, and hepatitis. The method used the Gabor wavelet transform and statistical moments to achieve a sensitivity of 85% in distinguishing normal from hepatitis liver images and 86% in distinguishing normal from cirrhosis liver images.

5. DEEP LEARNING IN MEDICAL ANALYTICS

Deep learning is a subfield of machine learning that has recently attracted a lot of interest due to its ability to automatically extract characteristics from unprocessed data [13]. It is possible that deep learning might be used to perform tasks like categorization, object recognition, and organ segmentation on ultrasound images [4]. The fetus [[14], [14], [15]], the heart [16], the breast [17], the prostate [18], the thyroid [19], the liver [13, 20], the brain [21], the spine [22], the bone [23], the carotid [24], the intravascular [25], the lymph [26], the muscle [27], and the kidney [28] are all examples of current uses of deep learning in doppler ultrasound analysis. Several different types of deep learning network designs have been applied to medical ultrasound analysis [4], including convolutional neural networks, deep belief networks, completely convolutional networks, hybrids of numerous network architectures, recurrent neural network (rnn), and auto-encoders.

6. RESEARCH PERSPECTIVES AND METHODOLOGY

The purpose of this research is to see if dynamic ultrasound images can be used to reliably classify liver state (normal, hepatitis, and cirrhosis liver) using deep learning methods. This was accomplished by training two-class (normal/cirrhosis, normal/hepatitis, and cirrhosis/hepatitis) and three-class (normal/cirrhosis/hepatitis) classifiers to differentiate between liver images. Next, a hybrid classifier is presented, which takes the weighted probabilities of the classes generated by each classifier and chooses the class with a majority voting approach.

7. DATASET FOR TRAINING

Liver biopsies were utilized to identify 210 images (70 normal, 70 hepatitis, and 70 cirrhosis). The input ultrasound liver images were prepared by a radiologist with experience in this field so that the classification task could be carried out. Manual cropping and resizing of images focused on the liver was done. Before submitting the images to the network, a square window is extracted from the desired liver area to maintain resolution and aspect ratio in the lateral and axial orientations. The target region is selected so that it includes the vast majority of liver tissue. More ultrasound image instances may be acquired with the help of enhancement, as will be shown in the next sections. Some examples of classified images are displayed here

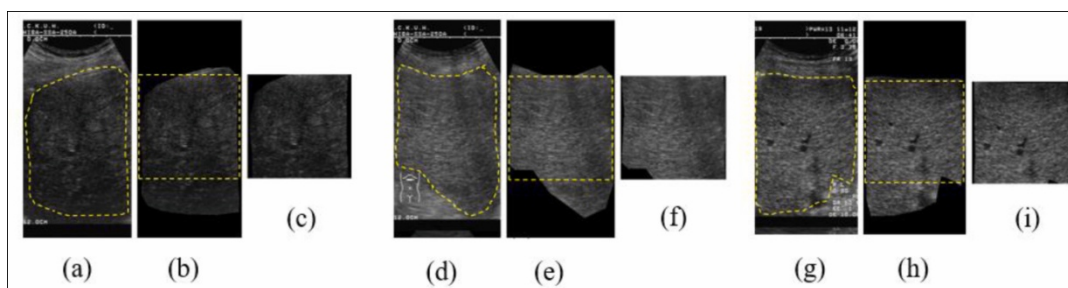


FIGURE 1. Ultrasound Images for Classification and Model Building

8. IMAGE ENHANCEMENT AND AUGMENTATION

With the help of data augmentation, networks won't overfit by memorizing every nuance of the training images rather than learning to uncover the underlying patterns. The network's resilience to image data distortions is also improved by the augmentation. As an example, random rotations can be introduced to the training inputs to make the training process robust against input image rotations.

The presented work performed (1) lateral and vertical translations of 2 pixels with no padding and (2) left-right and up-down flips on each of the preprocessed images. Consequently, the original dataset now includes 1296 more images (augmented images) (consisting of 210 images).

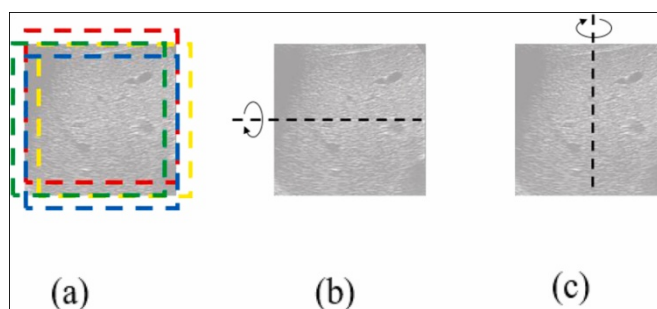


FIGURE 2. Image Augmentation and Enhancement

9. DESIGNING A NEURAL NETWORK WITH A DEEP LEARNING LAYER

The CDNN received the final modified ultrasound images detailed in the preceding sections, and the max-pooling layer down-sampled the input by splitting it into rectangular pooling areas and calculated the maximum value in each sector. The number of learnable parameters is decreased by these pooling layers, which in turn eliminates the possibility of overfitting. Next, the output consists of a single value for each ultrasound image that was used as input. Each iteration of the training process involves a both forward and backward trip across the network. The forward pass is the part of the training process when each layer uses its encoder to produce new outputs based on the preceding layer's results. Take, for example, a layer that receives X_1, \dots, X_n from the layer below it and generates Z_1, \dots, Z_m as its outputs for the layer above it. At the end of each forward pass, the loss function L is computed between the authentic goals T and the predictions Y . In the backpropagation, each layer uses its output derivatives to calculate the input variations of the loss L with regard to its weights. The derivatives of a loss may be computed using the chain rule, which is as follows:

$$\frac{\partial L}{\partial X^{(i)}} = \sum_j \frac{\partial L}{\partial Z_j} \frac{\partial Z_j}{\partial X^{(i)}} \quad i = 1, \dots, \text{number of inputs and } j = 1, \dots, \text{number of outputs}$$

$$\frac{\partial L}{\partial W_i} = \sum_j \frac{\partial L}{\partial Z_j} \frac{\partial Z_j}{\partial W_i} \quad i = 1, \dots, \text{number of learnable parameters and } j = 1, \dots, \text{number of outputs}$$

In convolutional deep neural networks, the Rectified Linear Unit (ReLU) layer is utilised as an activation function. Any input value that is less than zero is transformed into zero using a threshold operation. As an additional measure, a batch normalisation layer has been implemented to standardise the input of each layer throughout a mini-batch, which both accelerates training and decreases the network's sensitivity to its initialization. The iterative process of trial and error led to the selection of a learning rate of 0.0001. In the initial convolutional layers of a convolutional neural network, characteristics like colour and edges are taught to the network. By mixing the characteristics retrieved in prior convolutional layers, the network learns to recognise increasingly complex features.

10. KNOWLEDGE TRANSFER

It is typical practice for deep learning programmers to employ transfer learning. If a network has already been taught on one activity, it may be utilized as a foundation to learn another. For scenarios with a low number of images, training a network from start with randomly initialized weights is typically significantly slower and more complex than fine-tuning a network with transfer learning [29].

AlexNet [30], VGGNet [31], ResNet [32], and ResNeXt [33] are only few examples of pre-trained image classification networks that have learnt rich feature representations applicable to a broad variety of images. More than a million images from over a thousand item categories are used to train these networks [34–36] in the ILSVRC subset of the ImageNet database.

To facilitate transfer learning, we employed these networks. These pre-trained networks have their final layers optimized for 1000 classes. So, they need to be remolded and adjusted for the specific categorization job at hand. Figure 4 depicts the fully connected networks (FCNs) that we used to replace the last layers of these networks.

11. HYBRID CLASSIFIER BASED APPROACH

In this research, we trained four classifiers to distinguish between healthy, cirrhotic, and hepatitis-affected liver images. The first three classifications distinguished between normal and cirrhosis, normal and hepatitis, and cirrhosis and hepatitis; the last classifier separated ultrasonic liver images into these three types of liver illnesses. Based on these classifications, it is clear that two-class classifiers are superior to three-class classifiers, which do not provide enough classification power. To solve this problem, a hybrid classifier was developed [37–39] that would combine the findings of all trained classifiers by assigning different weights to the probability of the classifications that each classifier would provide. This was accomplished by using a soft - max layer in each classifier to distribute input probabilities over all classes.

A final class label was determined by averaging the weighted probabilities from all classifiers. We utilized a grid search with a step size of 0.125 to find the optimal weights for the outcome of each classifier, and then we choose the best

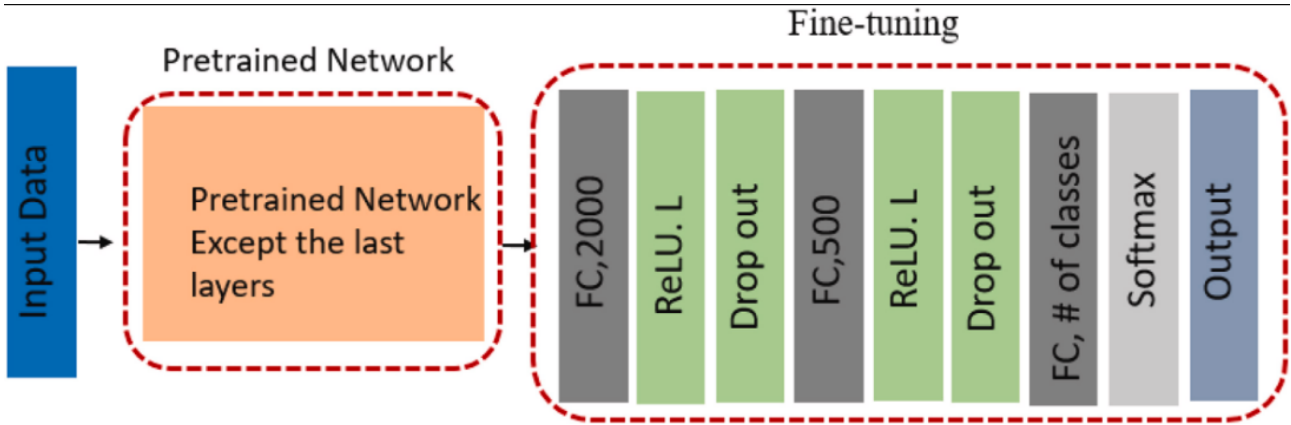


FIGURE 3. Architecture of the Presented Model

configuration based on its classification performance. Later, the sum of all weights was divided by each ideal weight in order to standardize them.

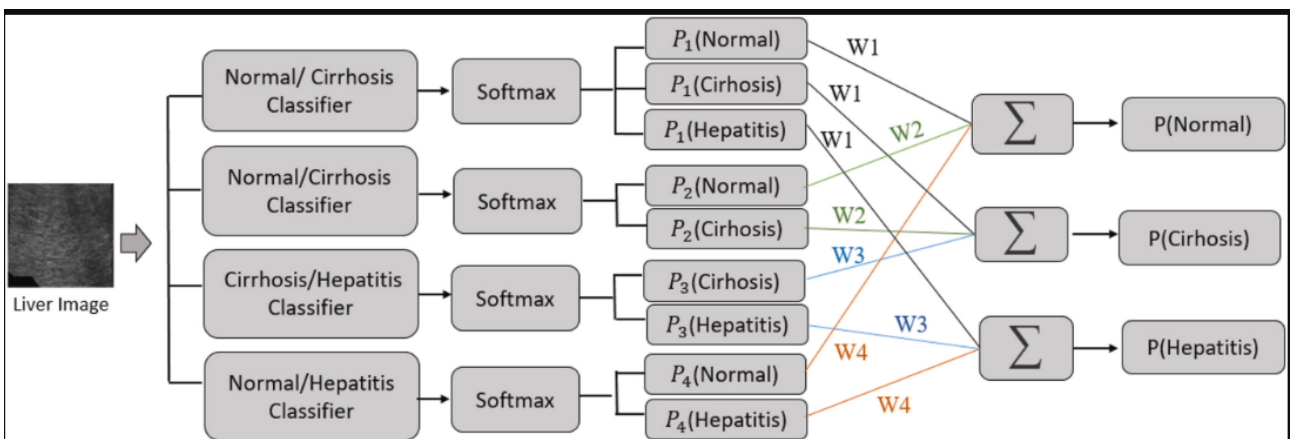


FIGURE 4. Framework of the Presented Model

12. RESULTS AND CONCLUSIVENESS OF EXPERIMENTS

In this part, we provide the findings from a study that used dynamic ultrasound images and deep learning algorithms to evaluate the classification performance of three different liver statuses: normal, hepatitis, and cirrhosis.

A total of 216 ultrasounds were analyzed, divided evenly between three groups (normal liver ultrasound, hepatitis, and cirrhosis) based on biopsy results. We created a 70% training set and a 30% validation set at random. Using 70% of the original dataset with augmentation for training and 30% of it without augmentation for validation, ResNet50 was trained using the modified FCN. It is frequently helpful to keep tabs on the training process as we put deep learning networks through their paces. For instance, we may ascertain the rate of improvement in network accuracy and check for signs of overfitting the training data or being stuck in a local minimum.

Accuracy of 59.09% is achieved after training the suggested CDNN from scratch for the categorization of liver images into three classes. Table 2, column 2 displays the diagnostic performance of a few well-known networks for three-class classification: ResNet50, ResNext, ResNet18, ResNet34, and AlexNet. Table 1, column 3 displays the same diagnostic findings for two-class classifiers employing these networks. Confusion matrices for ResNet50's discrimination between normal and cirrhosis, normal and hepatitis, and cirrhosis and hepatitis are displayed in Fig. 7. Table 2 also shows the experimental outcomes of the hybrid classifier.

However, pre-trained networks may be used as a foundation for extracting rich characteristics from liver images. The classification step may be better adapted to the job at hand via retraining the final fully-connected layers, which improves the results significantly. While the accuracy gained by using a three-class model was not satisfactory. In particular,

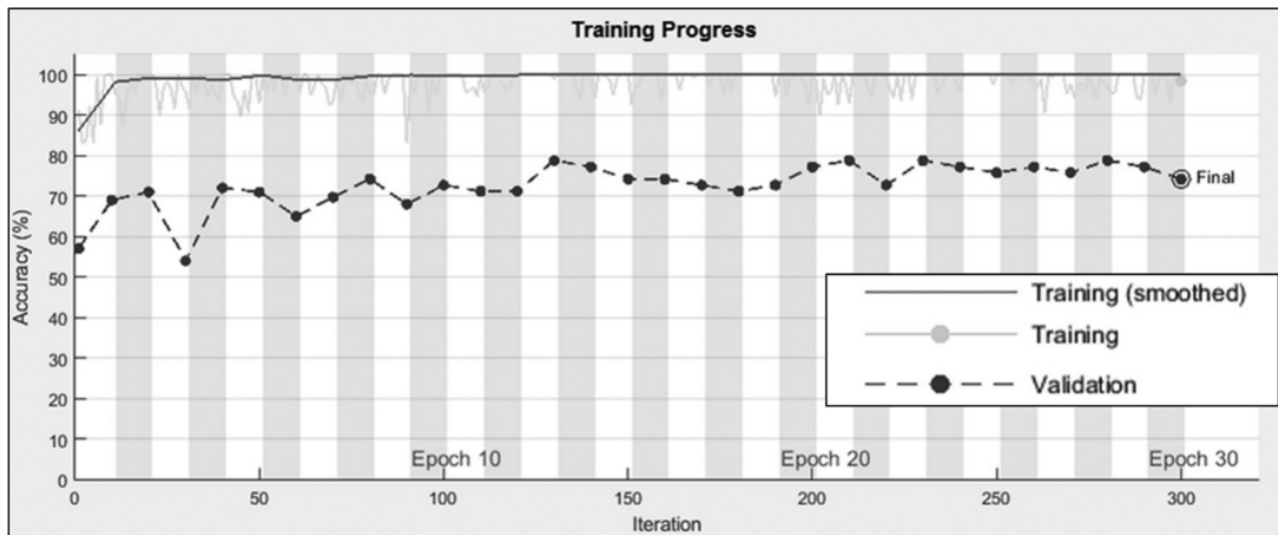


FIGURE 5. Training and Validation Aspects

Table 1. Analytics of Outcomes

Models	Sensitivity	Accuracy	Specificity	Groups
Resnet50	91.6%	88.6%	86.4%	Normal (1) / Cirrhosis
	91.6%	86.4%	81.8%	Normal (1) / Hepatitis (2)
	100%	88.6%	77.2%	Cirrhosis / Hepatitis (2)
ResNext	86.4%	79.5%	72.7%	Normal (1) / Cirrhosis
	86.2%	88.6%	91.6%	Normal (1) / Hepatitis (2)
	91.6%	93.2%	95.4%	Cirrhosis / Hepatitis (2)
ResNet18	91.6%	88.6%	86.2%	Normal (1) / Cirrhosis
	77.2%	84.0%	91.6%	Normal (1) / Hepatitis (2)
	91.6%	93.2%	95.4%	Cirrhosis / Hepatitis (2)
ResNet34	81.8%	79.5%	77.2%	Normal (1) / Cirrhosis
	86.2%	86.2%	86.2%	Normal (1) / Hepatitis (2)
	77.2%	86.2%	95.4%	Cirrhosis / Hepatitis (2)
AlexNet	91.6%	84.1%	77.2%	Normal (1) / Cirrhosis
	95.5%	86.4%	77.2%	Normal (1) / Hepatitis (2)
	91.6%	84.1%	77.2%	Cirrhosis / Hepatitis (2)

ResNet50 outperforms its competitors in two-class classification when sensitivity requirements are taken into account.

Accuracy demonstrated by ResNeXt and ResNet18, respectively, when differentiating between cirrhosis and hepatitis. Three-class classification results showed that ResNeXt’s highest achievable accuracy was less. In light of these findings and the findings for two-class classifiers, the authors settled on combining classifiers. With this goal in mind, we suggest a majority voting approach using a hybrid classifier to combine the probabilities of the predictions made by the various classifiers. Based on the outcomes, it’s clear that the hybrid classifier has the potential to boost the overall precision.

Table 2. Analytics of Accuracy Levels

Model	Classical Classifier	Accuracy of Proposed Hybrid Classifier
ResNet50	76.8%	88.2%
ResNeXt	81.3%	86.5%
ResNet18	73.2%	83.8%
ResNet34	72.2%	79.3%
AlexNet	72.2%	81.3%

We conducted studies utilizing a deep neural network model to sort ultrasonic liver images into normal, hepatitis, and cirrhosis categories. The results highlight the fact that deep features may be employed effectively for classification tasks and are replete with information. These findings suggest that a lack of sufficient data makes it impossible to successfully train a CDNN network from scratch.

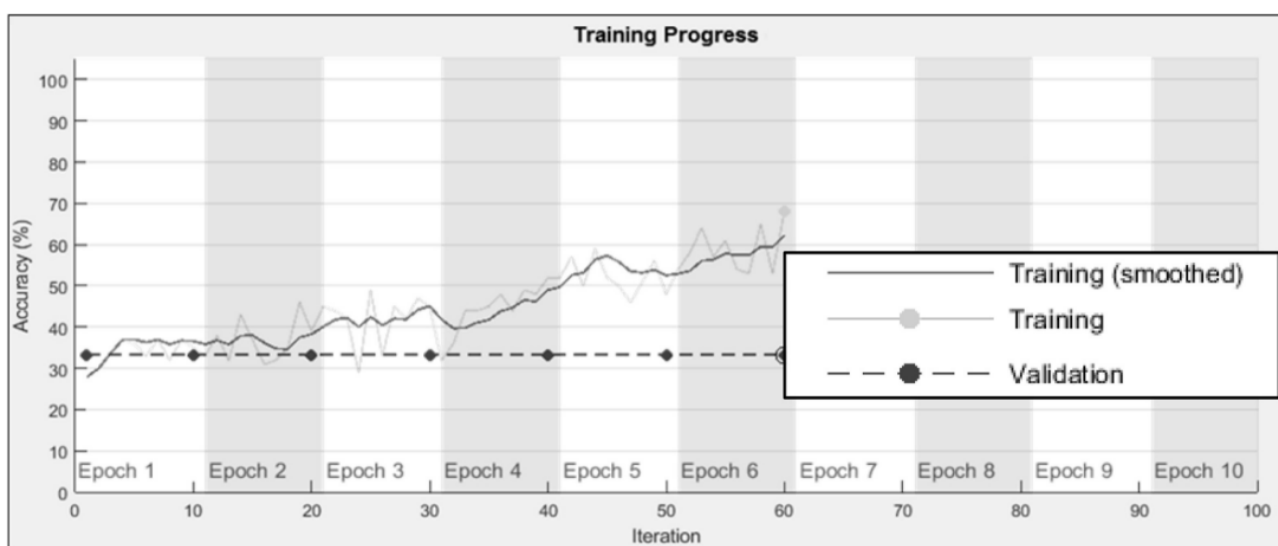


FIGURE 6. Training Progress and Outcomes

Segmenting the liver portions that were manually cropped as irregular polygons and feeding them into the network as binary objects ensured that they did not affect the classification results or the learning process. The network was unable to identify any significant regularities within these patterns. The use of the same dataset is necessary for a fair comparison of the classification performance to prior efforts. Because most prior research has only differentiated between normal and cirrhosis, hepatitis, or fatty liver. Quantitatively, these findings are in line with those published by Ahmadian et al. [12], who found that the cutoffs for detecting normal and cirrhosis were about 86% and 79%, respectively. They also reported results of 85% for normal and 77% for hepatitis differentiation. In comparison to their work, where a very constrained region of focus was chosen by an untrained researcher, our findings demonstrate superior categorization ability. In contrast, we employ a bigger region of tissue from liver imaging, which yields more objective and reliable results. Testing the suggested method’s performance on huge datasets is essential for determining its practicality. In each matrix, the negative predictive values shown in the second row indicate how well the model can predict in typical situations. Using the model for screening rather than diagnosis is recommended due to the model’s higher NPVs compared to the relevant PPVs.

13. CONCLUSION

The limited size of the sample is the study’s biggest flaw. Better results can be achieved in future studies by utilising a big dataset and integrating deep features with textural characteristics. Effective classifiers may be built on the tiny medical

datasets by fine-tuning an existing deep convolutional neural network, such as ResNeXt, ResNet18, ResNet34, ResNet50, or AlexNet. In this research, we offer a novel framework based on a hybrid classifier for separating healthy, cirrhotic, and hepatitis-affected liver images. These liver images were used to train two-class (normal/cirrhosis, normal/hepatitis, and cirrhosis/hepatitis) and three-class (normal/cirrhosis/hepatitis) classifiers. Since two-class classifiers outperformed three-class classifiers, a hybrid classifier is developed to combine the weighted probability of the classes from each classifier. The class with the highest cumulative score is then chosen through a majority vote process. Further tweaking of the CNN and the use of a bigger dataset is required to increase performance and resilience.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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