International Journal of Multidisciplinary Research and Growth Evaluation.

Diagnosis of Fatty Liver Using a Hybrid Approach of Deep Learning and Ensemble Learning

Hasanain Hayder Razzaq
Jabir Ibn Hayyan University for Medical and Pharmaceutical Sciences, 54001, Najaf, Iraq

* Corresponding Author: **Hasanain Hayder Razzaq**

Article Info

ISSN (online): 2582-7138
Volume: 05
Issue: 06
November-December 2024
Received: 12-10-2024
Accepted: 11-11-2024
Page No: 583-592

Abstract
Fatty liver disease is one of those health problems which, if not taken seriously, might lead to the most menacing complications. Henceforth, the diagnosing phase has to be both accurate and just-in-time to allow proper treatment. The approach based on the usage of the convolutional neural network AlexNet for feature extraction of a complex nature and decision-making by the AdaBoost classifier is hence introduced. Extremely high capability of feature extraction by AlexNet made its implementation reach a detection accuracy of 88.5%, in general 5% better than earlier practices. Results have proven that this approach can extract unique features from ultrasound images, which would be useful in diagnosing and managing fatty liver diseases. This could be instrumental in helping the physicians to be right on the spot in the accuracy and quality of diagnosis.

DOI: https://doi.org/10.54660/.IJMRGE.2024.5.6.583-592

Keywords: Diagnosis of fatty liver disease, ultrasound images, Alex net neural network, deep neural network, Adaboost algorithm

Introduction
With the increasing prevalence of fatty liver disease, it has become a significant global health concern due to its potential to lead to severe liver complications and other systemic disorders. Early and accurate diagnosis is essential for managing this condition and preventing its progression. Traditional diagnostic methods, such as biopsy and blood tests, are often invasive, time-consuming, or insufficiently precise [1]. Recently, advancements in medical imaging, particularly ultrasound, have opened new avenues for non-invasive diagnosis of fatty liver disease. However, manual interpretation of ultrasound images is prone to subjectivity and variability among clinicians, which may affect diagnostic accuracy [2]. This underscores the necessity of automated diagnostic systems that combine the power of deep learning techniques with robust classification methods to enhance precision and reliability. Leveraging the feature extraction capabilities of convolutional neural networks like AlexNet, paired with advanced classifiers such as AdaBoost, offers a promising solution for addressing these challenges.
Numerous studies have explored different approaches to enhance fatty liver detection using Ultrasound images.
In article [3], the authors diagnosed fatty liver disease through ultrasound images using deep convolutional learning. In this study, 90 ultrasound images from fatty liver patients and 51 images from healthy individuals were used. The models trained on combined liver-kidney-liver (CLKL) images achieved an accuracy of 80.1%, sensitivity of 86.2%, and specificity of 80.5% in detecting fatty liver disease. The regression model also showed a moderate accuracy ($R2 = 0.633$) in predicting fat fraction values, indicating the potential of deep learning-based ultrasound for diagnosing fatty liver disease.
In article [4], the authors developed neural network-based models to detect and classify the severity of Non-Alcoholic Fatty Liver Disease (NAFLD) using B-mode ultrasound images. This study compared several pre-trained convolutional neural networks, with ResNet-50 v2 achieving the best performance. The final model showed high diagnostic accuracy with an ROC area of 0.985 for detecting any severity and 0.996 for moderate to severe steatosis. These results suggest that this model works with non-invasive, cost-effective methods, offering a feasible alternative for clinical applications. However, challenges like device variations and motion artifacts should be addressed.

In article [5], the authors developed a machine learning (ML) model to differentiate Non-Alcoholic Fatty Liver Disease (NAFLD) from healthy liver tissue in children using ultrasound image texture analysis. The study utilized texture features extracted from regions of interest (ROI) in the ultrasound images, analyzed with ImageJ and MAZDA software. The final model, a combination of support vector machine algorithms, neural networks, and gradient boosting, achieved high accuracy in distinguishing NAFLD from normal liver images. The study highlights the potential of ML models using texture features for precise NAFLD classification.

In article [6], the authors propose a new computer-aided diagnosis (CAD) framework for detecting fatty liver disease using convolutional neural networks and transfer learning with a pre-trained VGG-16 model. This framework achieved a classification accuracy of 90.6% for detecting fatty liver and normal images, providing better diagnostic efficiency and further supporting radiologists in patient management.

In article [7], the authors proposed a convolutional neural network (CNN) for detecting fatty liver disease, tailored to the features of B-mode ultrasound images. Experimental results show that the CNN-based model achieved satisfactory classification performance and outperformed traditional methods for classifying fatty liver ultrasound images, emphasizing the potential of CNNs in improving diagnostic accuracy.

In [8], authors implemented deep learning in the detection of NAFLD via ultrasound images. A total of 710 ultrasound images of NAFLD were classified using three models of convolutional neural network (VGG16, ResNet50, and Inception-v3) to achieve accuracies of 66.2%, 58.5%, and 59.2%, respectively. Two new parameters were introduced to enhance the accuracies: ultrasound echo attenuation coefficient (θ), and ROD. A multi-input deep learning network was created based on the VGG16 model, combining ultrasound image analysis with θ and ROD, which showed strong diagnostic capacities (especially for moderate and severe fatty liver) with an AUC of 0.95 and 77.5% improved accuracy. The research thus paves the way for doctors to diagnose NAFLD accurately and efficiently by its methodology.

In reference [9], authors applied ultrasound in combination with artificial intelligence for the diagnosis of NAFLD as a non-invasive and cheap diagnostic tool. Only 120 clinically suspected NAFLD patients along with 10 healthy volunteers were considered for this study. MRI (MR-PDFF) determined the amount of fat in the liver as the reference standard. The ultrasonography images were taken for analysis from the 10 different sites of the liver lobes. A supervised machine-learning model was developed and tested. During the internal validation, the model recorded an accuracy of 0.941, recall at 88.2%, and precision at 89.0. For the test set, sensitivity exhibited by the model was 72.2%, specificity was 94.6%, PPV reached 93.1%, and the overall accuracy was 83.4%. These outputs hint that this AI-enabled ultrasound model might be used as a screening tool for NAFLD, particularly within high-risk populations.

In [10], the authors introduce a machine learning model for fatty liver disease (FLD) detection with multiple ultrasound images. Ultrasound has wide applications and is inexpensive; however, it often generates multiple images of the target tissue. A model is trained on these ultrasound images using a graph neural network after extracting features by a pre-trained image encoder. These embeddings produced are fed into a classifier for detecting FLD. The model was developed using a dataset of ultrasound images collected by Taiwan's Biobank. Better classifier performance was developed by the authors through consistent prediction under a risk control setting, ensuring high accuracy guarantees. This approach is aimed at increasing the dependability and diagnostic performance of detecting fatty livers from ultrasound images.

In [11], the authors contributed to the prediction of Non-Alcoholic Fatty Liver Disease (NAFLD) through machine learning algorithms. They also proposed an alternative method that combines traditional data augmentation with Generative Adversarial Networks to produce synthetic medical images for the extension of training datasets and model performances. Many deep neural network architectures were tried, and the most proper model achieved accuracy, recall, precision, and specificity of 96%, 93%, 95%, and 96%, respectively, outperforming models like SegNet. The study proved that synthetic images improve the effectiveness of GANs in the classification of NAFLD with real-world data, a very promising avenue in the prediction of liver diseases.

In reference [12], the use of machine learning techniques, particularly Generative Adversarial Networks (GANs), by the authors, for the prediction of NAFLD is discussed. The authors merge conventional data augmentation with synthetic images produced by GANs to increase the training dataset. This approach improved model performance, with the GAN-based model surpassing models such as SegNet, having an accuracy of 96%, recall of 93%, precision of 95%, and specificity of 96%. Which indicated that in the presence of both synthetic and real-world data, NAFLD classification was greatly improved and which can be a promising way to better predictions about liver diseases.

In the work [13], the focus is on the detection of Non-Alcoholic Fatty Liver Disease (NAFLD) from ultrasound (US) images. Digital image analysis (DIA) and machine learning (ML) have been used for the discrimination between healthy liver tissue and NAFLD-affected liver tissue. Models were two classifiers based on EfficientNet and K-Nearest Neighbors (KNN). The former achieved 87% accuracy, while the latter attained 85% accuracy. It has been revealed by this study that automatic detection of liver fat using texture-based features from the gray-level co-occurrence matrix (GLCM) can go a long way in enabling accurate diagnosis of NAFLD, thus proving to be quite helpful for physicians in the decision-making process.

In article [14], the authors discuss the increasing prevalence of Non-Alcoholic Fatty Liver Disease (NAFLD) and the challenges in its non-invasive diagnosis. While traditional methods like ultrasonography and clinical scoring systems have been suggested as alternatives to liver biopsy, their effectiveness has been questioned. This study evaluates the use of artificial intelligence (AI) to improve the diagnosis and quantification of NAFLD through ultrasound images. A systematic review of 49 studies shows that AI significantly enhances the diagnosis of NAFLD, Non-Alcoholic Steatohepatitis (NASH), and liver fibrosis. AI-supported systems showed improved accuracy, sensitivity, and specificity, but further prospective studies comparing AI with traditional methods are needed before real-world implementation.

The papers herein reviewed have as their principal area of challenge the doubtful capability of their models to recognize fatty liver disease from ultrasound images with any measure of correctness. They further include problems related to noise and motion artifacts that distort the acquired images. Also, challenges come about through variations in devices and imaging conditions; also, in specific cases, it has been pointed out that the models do not well identify different stages of the disease. There is also the need to improve the process of feature extraction from ultrasound images.

It uses the AlexNet convolutional neural network to address complex feature extraction in ultrasound images, with subsequent use by an AdaBoost classifier for improved accuracy and reduced diagnostic error in the task.

This combination marries well with the capability that AlexNet has in extracting rich and intricate features in images and further with AdaBoost's power in boosting the performance of machine learning models. The approach drastically enhances diagnostic speed, accuracy, and efficiency over than that of the usual methods — especially in more complicated cases of data and feature analysis. The sections below will follow this organizing structure: Section 2 will elaborate on the basic concepts required for better comprehension of the proposed methodology. Section 3 will introduce and explain the methodology, with details on the design of the CNN for feature extraction based on AlexNet and the AdaBoost classifier for disease classification. Section 4 will explain the dataset in detail, which includes ultrasound images and their labeled data for detecting fatty liver disease.

Section 5 will account for the choice of evaluation metrics through which any level of performance toward the proposed model can be estimated. Section 6 will report on the experiments, analyzing the achieved classification accuracies, senilities, specificities, and other related measures.

Section 7 closes by comparing the present method with a number found in the literature to showcase the best features of the present method.

Section 8 concludes and discusses results on fatty liver disease detection and possible future directions.

2. Basic concepts

This section deals with an elaborate discussion of the basic principles and key concepts that are necessary to understand the method of this work.

2.1. AlexNet

AlexNet is a pretrained deep convolutional neural network that can extract complex hierarchical features from images. The convolutional layers in this network extract visual features in a manner where low-level visual features are extracted progressively, such as edges and lines in the initial layers, and high-level features of more complexity-like shapes, patterns, and objects are obtained in deeper layers. Starting from the preprocessed images, the images are fed with the AlexNet architecture, and the output of the last layer before the fully connected layers is the extracted features from the images. These would be numerical vectors, quite high-dimensional normally. This neural network contains in total 11 layers. For the extractor of the features from the images in this work, only the top 8 layers will be taken into consideration. The following describes the layers in the architecture of this neural network for feature extraction [15].The layer architecture for feature extraction in AlexNet is as follows: Layer 1: 96 11×11 convolut ional layersLayer 2: Using 3×3 convolut ional layers Layer 3: 256 5×5 convolutional layers Layer 4: Using 3×3 convolutional layersLayer 5: 384 3×3 convolutional layersLayer 6: 384 3×3 convolutional layers Layer 7: 256 3×3 convolutional layers • Layer 8: This is a pooling layer with a size of 3×3. • Layer 9: Fully connected layer with a size of 4096. • Layer 10: Fully connected layer with a size of 4096. • Layer 11: Fully connected layer with a size of 1000.

The tasks performed by each of these layers are described in the following sections.

Layer 1: First Convolutional Layer This layer is a convolutional layer that takes as input an image of size 3×224×224. It applies 96 kernels of size 11×11 with a stride of 4 and padding equal to 2. The convolution operation is performed on the input image, and the output consists of 96 feature maps of size 55×55. These are then passed through a linear activation function and forwarded to the next layer.

Layer 2: First Pooling Layer The output of the first layer is passed to a pooling layer. Here, the pooling process is done using a kernel of size 3×3, stride of 2, and padding equal to 0. The output of this layer consists of 96 feature maps of size 27×27, which are passed to the next layer.

Layer 3: Second Convolutional Layer In this stage, the output from the previous layer (used as input for this layer) undergoes convolution with 256 kernels of size 5×5, stride of 1, and padding equal to 2. The output consists of feature maps of size 256×27×27, which are then passed through a linear activation function and forwarded to the next layer.

Layer 4: Second Pooling Layer It receives the output from the previous convolution layer and operates max-pooling with a 3×3 kernel, a stride of 2, and padding equal to 0. It will have 256 features of size 13×13 as its output, which will now be passed through a linear activation function to the next layer.

Layer 5: Third Convolutional Layer It takes the input as the output of the previous layer (256 feature maps of 13 x 13). Convolutions are performed with 384 kernels of size 3 x 3, a stride of 1, and padding equal to 1. The output will be comprising 384 feature maps of 13 x 13 which, before getting passed on to the next layer, are passed through a linear activation function.

Layer 6: Fourth Convolutional Layer This layer conducts the convolution operation on the output of the previous layer similar to what is done in Layer 5 convolution. It produces 384, 13x13 sized feature maps that are then linearly activated and passed onto the next layer.

Layer 7: Fifth Convolutional Layer These are again convolutions, but the kernel size is 3×3 with a total of 256 kernels, a stride of 1, and this time the padding is equal to 1 on the output from the previous layer. The output consists of 256 features maps of size 13×13 which are then passed through a linear activation function and fed to the next layer.

Layer 8: Third Pooling Layer This layer would take input from the previous layer (256 feature maps of size 13×13) and carries out pooling with kernel size 3×3, stride 2, padding same 0. It results in 256 feature maps of size 6×6, output of which is to given through linear activation function forwarded to the next layer.

2.2. Adaboost

The AdaBoost algorithm is one of the powerful and popular algorithms for data classification. It develops a decision tree that divides the training data into various classes, and test data are finally classified using this tree [16]. Steps in training the

AdaBoost algorithm are as follows [17]:

Begin Training: All the initial training data are taken as an input to the algorithm.

2. Feature Selection: In this step, the algorithm chooses appropriate features that can well separate the categories of the dataset. Features are selected on the basis of information gain or Gini. These parameters show how well each feature indicates the level of classification of the data being worked on.

3. Building the Decision Tree: A decision tree is built using the features that have been selected. The decision tree divides the data into different categories using conditional rules. Each node in the decision tree examines a feature, and based on the value of that feature, it directs the data to one of the branches of the tree.

4. Checking Stopping Conditions: At each stage of building the decision tree, stopping conditions are checked. These conditions could include factors such as the maximum depth of the tree, the minimum number of samples at each leaf, or the minimum population for each category. For example, if the maximum depth of the tree is set to 5, when the tree reaches a depth of 5, the tree-building process stops, and the final decision tree is obtained. Similarly, if the number of samples at any leaf is less than a minimum threshold, the tree might need to use a common label for those samples instead of a precise classification. In this case, the training stops, and the final decision tree is created. Properly setting the stopping conditions can improve the performance and efficiency of the AdaBoost algorithm.

5. Backtracking and Building Leaves: When a stopping condition is met, the decision tree returns to the backtracking step and labels the leaves. At this stage, each leaf belongs to a category, and its label is used as the output of the algorithm for test data. The final decision tree includes all the leaves that have fully classified the data.

6. Prediction and Evaluation: Using the constructed decision tree, we can predict the test data. By applying the test data to the decision tree, each data point is assigned to a specific leaf, and the corresponding label is displayed in the algorithm's output. Then, the algorithm's performance can be evaluated by comparing the predicted labels with the actual labels of the test data.

3. Methodology

In this paper, our goal is to diagnose fatty liver disease from ultrasound images. One of the most important steps in diagnosing this disease is feature extraction from images. To achieve this, we use the pre-trained convolutional neural network AlexNet. This neural network has been pre-trained on large datasets like IMAGE NET and does not require re-training. AlexNet consists of 11 layers, six of which are convolutional layers. The convolutional layers extract features from images using windowing.

In this study, instead of using fully connected layers for classification, the features extracted from this network are transferred to the AdaBoost algorithm for classification. Using this method allows us to improve classification accuracy because the fully connected layers actually function like a multi-layer perceptron, and using the AdaBoost classifier improves performance.

In the image preprocessing stage, the input images are first resized to 224x224 pixels. This is the standard size for input into the AlexNet convolutional neural network. Since the AlexNet convolutional neural network is insensitive to noise and lighting changes, this feature enhances its performance in detecting and classifying ultrasound images accurately and resiliently to lighting variations. After resizing the images, no impact from noise or lighting changes is applied to the detection process, and only the measurement of important features from the images is considered.

After preprocessing and resizing the images, the next step is feature extraction. In this step, the AlexNet neural network is used, which is specifically designed to extract complex and hierarchical features from images.

The convolutional layers of this network sequentially extract low-level visual features such as edges and lines, and as we progress to higher layers, more complex visual features such as objects and intricate patterns are identified. The features extracted from the higher layers are presented as high-dimensional numerical vectors. In this research, only the first eight layers of the AlexNet neural network are used for feature extraction.

After feature extraction, the features are normalized. Normalization means adjusting the features so that they have a zero mean and unit variance. This process improves the performance of classifiers and can resolve scalability issues, as shown in Equation 1. After normalizing the features, the data is split into training and testing sets. Typically, 70% of the data is used for training, and 30% is used for model evaluation and testing.

$$Z_i = \frac{X_i - \mu}{\sigma} \quad (1)$$

After extracting and normalizing the features, the AdaBoost classifier is used for data classification. AdaBoost is a well-known and powerful algorithm for classification, which divides the training data into several categories using decision trees and then uses them to classify the test data. Based on the features extracted from the AlexNet neural network, this algorithm is capable of accurately categorizing the data into different classes.

The flowchart of the proposed method can be seen in the following section

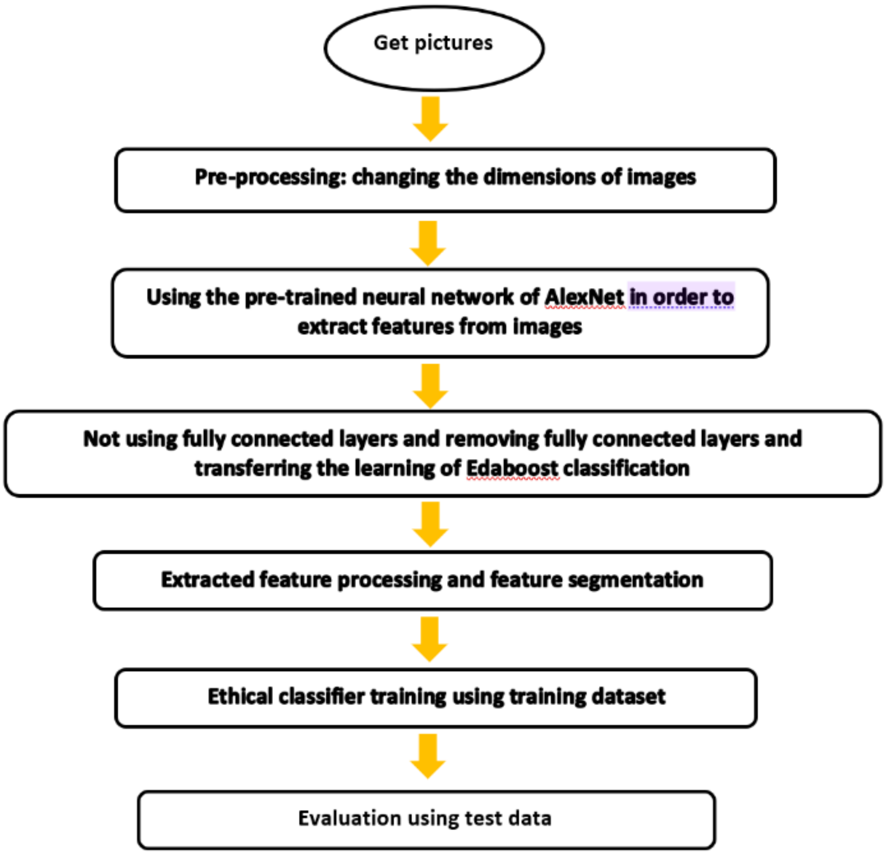

Fig 1: Flowchart of the proposed method

4. Dataset

In this paper, a database known as the Zenodo repository is used. This database can serve as a valuable resource for researchers interested in fatty liver imaging. It contains ultrasound images from 110 severely obese patients (40 men and 70 women) with an average age of 40.1 ± 9.1 years and an average body mass index of 45.9 ± 5.6, collected at the Medical University of Warsaw, Poland.

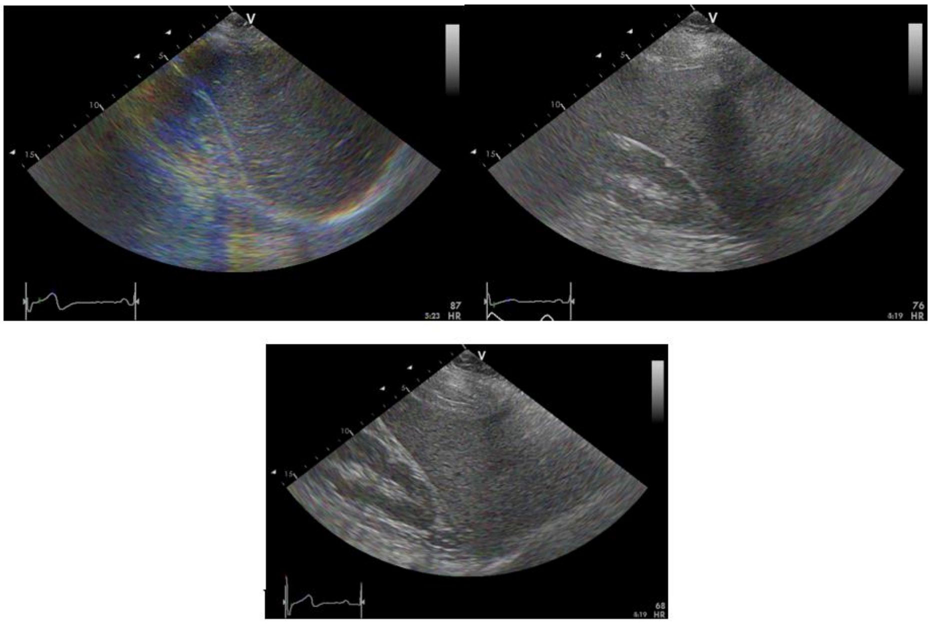

Fig 2: Part of the dataset images

5. Evaluation Metrics

In this paper, the following evaluation criteria are used to assess the performance of the proposed method in diagnosing fatty liver disease using ultrasound images:

1. Accuracy: The ratio of the number of samples correctly classified to the total number of samples.

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Negative}{TP+TN+FP+FN}$$

2. Coverage: The ratio of the number of positive samples correctly identified as positive to the total number of actual positive samples.

$$Recall = \frac{\sum True\ Positive}{\sum Realy\ Positive}$$

$$Precision = \frac{\sum TP}{\sum Test\ Outcome\ Positive}$$

3. Confusion Matrix: A matrix that shows the number of samples from each class that have been correctly and incorrectly classified.
These metrics can be useful in evaluating the accuracy and performance capability of the proposed method for detecting fatty liver disease from ultrasound images.

6. Simulation results

In this section, we will review the performance of the results of the proposed method in order to diagnose fatty liver disease.The simulations were conducted using MATLAB 2022 on a system with an Intel Core i5 cpu , 3 GB RAM
First, after receiving the images from the dataset, the preprocessing step must be performed. In this step, the dimensions of the images are resized to the appropriate size for input to the convolutional neural network, which is 224x224. In Figure 3, a sample of the read image and its resized version can be seen.

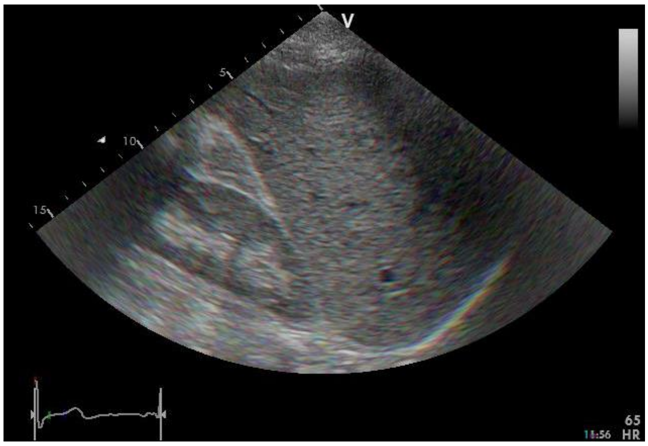

Fig 3: An example of the read and resized image

After preprocessing the images, the AlexNet neural network will automatically extract a 1000-dimensional feature vector. This vector contains potential features from the images that are obtained by the neural network during training, based on various optimization algorithms and utilizing all layers of the network. These features are typically representative of important information from the images and are used as input for classification. The features obtained from the neural network were normalized, and as a result, the feature values fall within the range between 0 and 1. A portion of the features after normalization is shown in Figure 4.

	1	2	3	4	5	6	7	8
1	0.0071	0.1749	0.0851	0.0414	0	0.0397	7.4113e-04	0.0591
2	0.0012	0.1005	0.0780	0.0343	0	0.0314	4.1489e-04	0.0366
3	0.0095	0.2163	0.0757	0	0	0.0275	7.9433e-04	0.0378
4	0.0012	0.1052	0.0780	0.0272	0.1111	0.0332	1.9740e-04	0.0248
5	0	0.1619	0.0473	0.0414	0.1986	0.0509	0.0027	0.0390
6	0.0059	0.1371	0.0875	0	0	0.0303	2.3759e-04	0.0355
7	0.0035	0.0922	0.0591	0.0378	0.1040	0.0366	2.9314e-04	0.0307
8	0.0118	0.1359	0	0	0	0.0417	1.5839e-04	0.0343
9	0.0024	0.2329	0.0827	0.0532	0.6418	0.0361	1.8676e-04	0.0626
10	0.0095	0.1478	0.1135	0	0	0	2.7423e-04	0.0638
11	0.0047	0.1300	0.1087	0	0	0.0444	2.2577e-04	0.0355

Fig 4: Part of the normalized features

After preparing and normalizing the features extracted by the AlexNet neural network, these features were provided to the AdaBoost classifier for classification. The specifications of the AdaBoost algorithm used in this paper are provided in Table 1.

Table 1: Adaboost classifier specifications

Algorithm Name	Classifier of Adaboost
The number of neurons in the input layer	1000 neurons in the input layer
The number of neurons in the output layer	2 neurons in the output layer
Goal	Improving Classification Accuracy and Performance by Combining Weak Classifiers
Training Process	Combining Multiple Weak Classifiers Using the AdaBoost Algorithm
Weak Classifier Performance	Calculating Classification Accuracy and Updating Weights
Strong Classifier	Combining weak classifiers based on their weights
Advantages	Reducing classification error, using each weak classifier
Training Steps	Determining initial weights, training weak classifiers, updating weights
Use in this thesis	Using the AdaBoost classifier for fatty liver disease detection

In the following section, we will review the results obtained for both the training and test datasets. The performance evaluation results of the proposed method for each dataset will be examined separately.

In Figure 5, the results of the training dataset are displayed in the form of a confusion matrix. This matrix is a 3x3 matrix, and each entry represents the number of correctly classified samples. The entries of this matrix are defined as follows:

Entry (1,1): The number of samples correctly classified as positive class (fatty liver disease).
Entry (1,2): The number of samples incorrectly classified as negative class (healthy liver).
Entry (2,1): The number of samples incorrectly classified as positive class.
Entry (2,2): The number of samples correctly classified as negative class
Additionally, based on the confuse on matrix, we can calculate other evaluation metrics. For example:
Accuracy: This metric shows the ratio of correctly classified samples to the total number of samples. The accuracy calculation based on the confusion matrix is as follows:
Accuracy = (Entry (1,1) + Entry (2,2)) / (Entry (1,1) + Entry (1,2) + Entry (2,1) + Entry (2,2))
Recall (True Positive Rate): This metric shows how well the classifier identifies actual positive samples. Recall calculation based on the confusion matrix is as follows:

Recall = Entry (1,1) / (Entry (1,1) + Entry (1,2))

Precision (Positive Predictive Value): This metric shows how well the classifier identifies positive samples that actually have the disease. Precision calculation based on the confusion matrix is as follows:
Precision = Entry (1,1) / (Entry (1,1) + Entry (2,1))
By examining the values of these metrics in the confusion matrix, we can more accurately assess how successful the proposed method is and how well it identifies fatty liver disease.

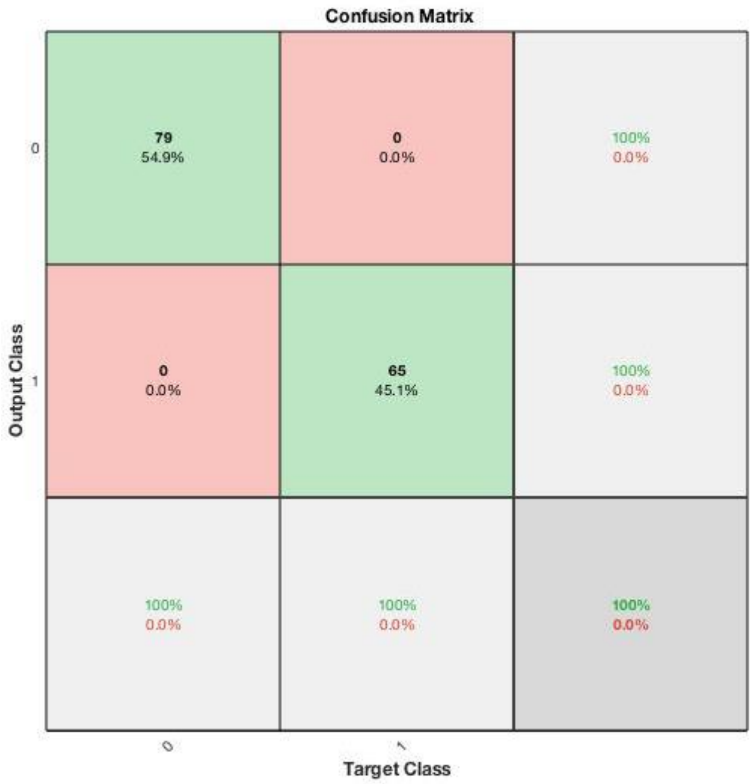

Fig 5: Confusion Matrix of the Training Dataset for the AdaBoost Classifier

As explained above, it can be observed that the accuracy obtained for the training dataset is 100%. This indicates that the AdaBoost classifier has been able to correctly adjust its parameters using the training dataset.
Analysis of Results Obtained from the Test Dataset
In order to analyze and evaluate the results of the proposed method, the test dataset was used as input to the AdaBoost classifier, and the results are presented in the form of figures and charts.
Figure 6 shows the results related to the test dataset in the form of a confusion matrix. Based on the previous section, it can be stated that the percentage of data correctly classified into the fatty liver class is 59%, the percentage of data in the healthy class is 29.5%, 4.9% of the data were mistakenly classified into the fatty liver class, and 6.6% were mistakenly classified into the healthy class. Finally, the obtained accuracy is 88.5%.

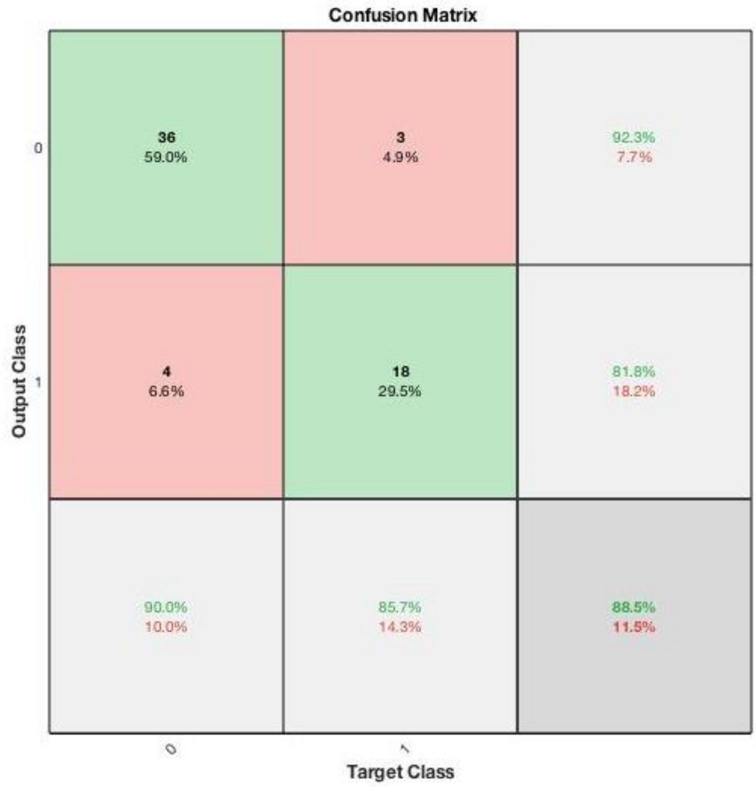

Fig 6: Confusion Matrix of AdaBoost Classifier on the Test Dataset

In Figure 7, the results for the test dataset are presented based on the Receiver Operating Characteristic (ROC) curve. The ROC curve represents the ratio of true positives to false positives for the AdaBoost classifier. In this curve, the higher the curves are above the 45-degree line, the more accurate the classifier is in distinguishing between correct and incorrect predictions. Ultimately, this indicates that the classifier has classified the test data with greater accuracy.

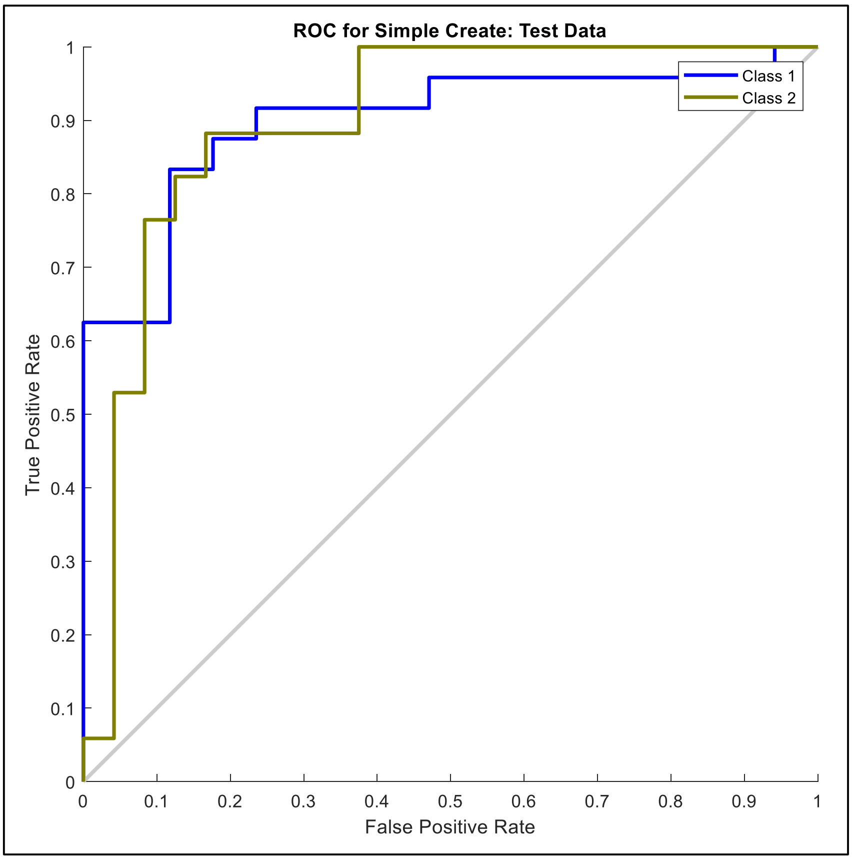

Fig 7: ROC Curve for Test Data

The results obtained for the test data metrics are shown in Figure 8. According to this graph, the accuracy of the test data is 88.25%. This metric indicates that 88.25% of the test samples were correctly classified by the classifier.
Additionally, the precision for the test data is 92.3%. This metric shows that 92.3% of the instances predicted as positive by the classifier are indeed positive.
The recall for the test data is 90%. This metric indicates that 90% of the actual positive samples were correctly identified by the classifier. Finally, the F1 score is 91.1%. The F1 score is a combined metric that takes both precision and recall into account and is calculated as the geometric mean of precision and recall. A high F1 score of 91.1% suggests that the classifier performs well.

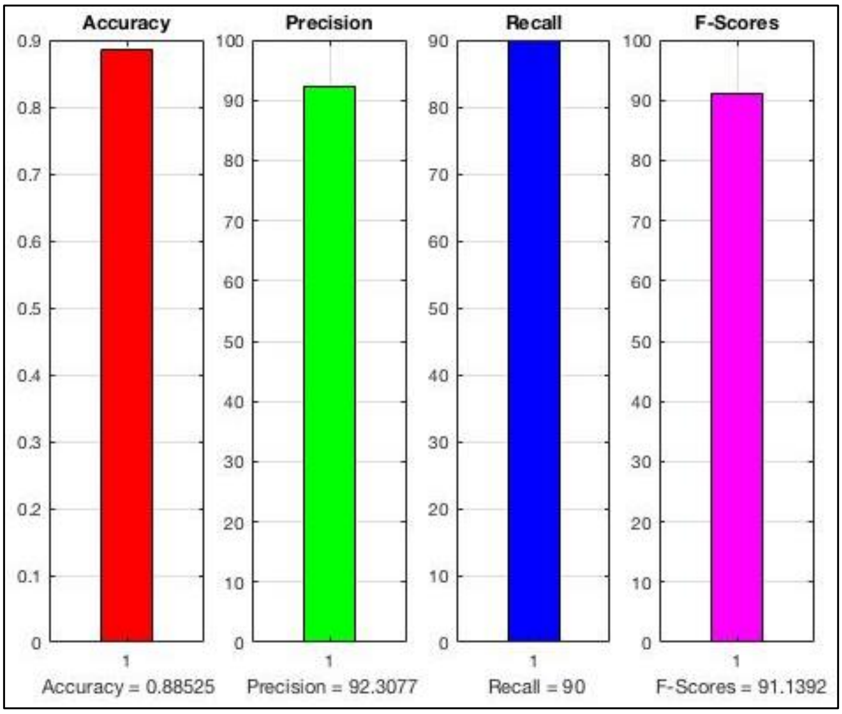

Fig 8: Evaluation Metrics Results for the Test Dataset

Overall, based on the obtained results, the proposed method for detecting fatty liver disease using ultrasound images demonstrates good performance and is capable of accurately classifying the test samples.

7. Comparison

In Table 2, the results for the test data obtained with Adaboost classifier are compared with other state-of-the-art methods. All works have used the same dataset; that is the reason for this note of comparison required to be specified here.

Accuracy	method
82.65%	NB[18]
76.96%	LR[18]
81.85%	ANN[18]
88.5%	Alexnet+Adaboost

Results in Table 2 indicate that, by using the AlexNet neural network and AdaBoost classifier with a feature extraction method, an average 5% enhanced level of accuracy is obtained for the feature described over those other methods presented. The reason for such a difference in accuracy is that the powerful, deep etwork AlexNet can extract very complex features, in addition to the AdaBoost classifier, which enhances the accuracy of diagnoses of liver disease to a great extent. Such results can state that the approach to the rule paper must be approved as an effective and superior one for diagnosis liver disease.

8. Conclusion

Fatty liver disease is considered as one of the most common precursors to severe liver pathologies and general health-related complications. The identification of this disease, with the highest quality and least loss of information, is very important for its further effective and optimal treatment. Innovations in this field and the possibility of seeing resulted ultrasound sections on technological monitors opened up some new opinions for diagnosing such a disease as fatty liver. Previous studies offer some points of view on research designed for diagnosing fatty liver using ultrasound imaging. In proceeding work on this subject, various features are juxtaposed using traditional approaches, for instance by Support Vector Machine (SVM), the nearest neighbors of a point, or simple neural networks. In some cases, classification is performed by routine methods such as decision trees and fuzzy logic. It is admitted that these methods are very simple and apply, but do not give more than that in terms of diagnostic accuracy.
This paper discusses the method of diagnosis of hepatic steatosis through ultrasound images. Diagnosis of the hepatic steatosis achieved good results by using the AlexNet neural network for feature extraction and the AdaBoost classifier for decision-making.
When we used AlexNet neural network features for the extraction and AdaBoost classification decision-making, we achieved 78% accuracy in detecting fatty liver disease. The most important advance over previous works in this field is the use of the AlexNet neural network. Being a deep network capable of extracting complex and non-linear characteristics from images, it brought a huge increase in diagnostic accuracy of fatty liver disease. The experimental results gave

the accuracy of 88.5% for this method, which is 5% more than for others. On the whole, with the developed approach, meaningful information that made up unique features of ultrasound images on the topic of fatty liver disease was obtained. The method can be very helpful to physicians and healthcare specialists in making information relevant to improved diagnostic and treatment decision processes.

9. References

1. Cao W, An X, Cong L, Lyu C, Zhou Q, Guo R. Application of deep learning in quantitative analysis of 2-dimensional ultrasound imaging of nonalcoholic fatty liver disease. Journal of Ultrasound in Medicine. 2020;39(1):51-59.
2. Atabaki-Pasdar N, Ohlsson M, Viñuela A, Frau F, Pomares-Millan H, Haid M, et al. Predicting and elucidating the etiology of fatty liver disease: A machine learning modeling and validation study in the IMI DIRECT cohorts. PLoS Medicine. 2020;17(6):e1003149.
3. Kim T, Lee DH, Park EK, Choi S. Deep learning techniques for fatty liver using multi-view ultrasound images scanned by different scanners: Development and validation study. JMIR Medical Informatics. 2021;9(11):e30066.
4. Chou TH, Yeh HJ, Chang CC, Tang JH, Kao WY, Su IC, et al. Deep learning for abdominal ultrasound: A computer-aided diagnostic system for the severity of fatty liver. Journal of the Chinese Medical Association. 2021;84(9):842-850.
5. Das A, Connell M, Khetarpal S. Digital image analysis of ultrasound images using machine learning to diagnose pediatric nonalcoholic fatty liver disease. Clinical Imaging. 2021;77:62-68.
6. Reddy DS, Bharath R, Rajalakshmi P. A novel computer-aided diagnosis framework using deep learning for classification of fatty liver disease in ultrasound imaging. In: 2018 IEEE 20th International Conference on E-Health Networking, Applications and Services (Healthcom). IEEE; 2018. p. 1-5.
7. Zhang L, Zhu H, Yang T. Deep neural networks for fatty liver ultrasound images classification. In: 2019 Chinese Control and Decision Conference (CCDC). IEEE; 2019. p. 4641-4646.
8. Liu Y, Yu W, Wang P, Huang Y, Li J, Li P. Deep learning with ultrasound images enhances the diagnosis of nonalcoholic fatty liver. Ultrasound in Medicine & Biology. 2024;50(11):1724-1730.
9. Tahmasebi A, Wang S, Wessner CE, Vu T, Liu JB, Forsberg F, et al. Ultrasound-based machine learning approach for detection of nonalcoholic fatty liver disease. Journal of Ultrasound in Medicine. 2023;42(8):1747-1756.
10. Yen TJ, Yang CT, Lee YJ, Chen CH, Yang HC. Fatty liver classification via risk-controlled neural networks trained on grouped ultrasound image data. Scientific Reports. 2024;14(1):7345.
11. Paul G, Ramkumar G. A novel and robust fatty liver recognition method based on hybrid generative adversarial networks on ultrasound images. In: 2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES). IEEE; 2023. p. 1-6.
12. Inamdar SW, Subasi A. Artificial intelligence–based fatty liver disease detection using ultrasound images. In: Applications of Artificial Intelligence in Healthcare and Biomedicine. Academic Press; 2024. p. 175-204.
13. Paul G, Govindaraj R. Experimental analysis for non-alcoholic fatty liver disease in ultrasound images based on efficient net classifier. In: 2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES). IEEE; 2023. p. 1-7.
14. Alshagathrh FM, Househ MS. Artificial intelligence for detecting and quantifying fatty liver in ultrasound images: A systematic review. Bioengineering. 2022;9(12):748.
15. Alom MZ, Taha TM, Yakopcic C, Westberg S, Sidike P, Nasrin MS, et al. The history began from AlexNet: A comprehensive survey on deep learning approaches. arXiv Preprint. 2018. arXiv:1803.01164.
16. Schapire RE. Explaining AdaBoost. In: Empirical Inference: Festschrift in Honor of Vladimir N. Vapnik. Springer Berlin Heidelberg; 2013. p. 37-52.
17. An TK, Kim MH. A new diverse AdaBoost classifier. In: 2010 International Conference on Artificial Intelligence and Computational Intelligence (AICI). IEEE; 2010. p. 359-363.
18. Wu CC, Yeh WC, Hsu WD, Islam MM, Nguyen PAA, Poly TN, et al. Prediction of fatty liver disease using machine learning algorithms. Computer Methods and Programs in Biomedicine. 2019;170:23-29.