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CLASSIFICATION OF LIVER DISEASE (NORMAL OR AB NORMAL) BASED ON CNN

Aqeela N. Abed
Coputer Department
College of Medicin\ AL-Iraqia University
Baghdad,Iraq

Prof. Hafedh Trabelsi
Deptement de Génie Electrique
,l'Ecole Nationale d'Ingénieurs de Sfax
Rte de Soukra Km 3.5, BP 1173,
CP 3038, Sfax, Tunisie

***ABSTRACT*— Liver disease is one of the main challenges that people face in preventing diseases, it causes many complications that must be detected early and treated in a timely manner. In the field of automatic diagnosis of the liver through sonar images (ultrasound). But one of the most important problems, including problems related to a smaller amount of data, and other pathological pictures of different severity are similar, Ultrasound imaging is necessary for the non-invasive diagnosis of liver diseases as advanced diagnosis reduces the number of deaths in ultrasound liver diseases such as cirrhosis and liver cancer. Interpretation of images remains a challenge as appropriate expertise in this field may not do so, and in response here we highlight an image-classification convolutional neural network (CNN) for liver disease detection in images of ultrasound as an initial application. Therefore, in this paper, the proposal of a classification method through a convolutional neural network based on the features of liver ultrasound images that are taken by pixel level. the normal and abnormal liver images can be diagnosed automatically with ultrasound. The proposed method improved the classification accuracy by solving the problem of less data amount that gained. The present proposed experimental method has a better accuracy than the other classification methods compared with the other learning and traditional methods.**

KEYWORDS— Liver case, Machine learning, Classification, Ultrasound images

1- INTRODUCTION

The purpose of medical imaging methods by using ultrasound (US) is one of the most generally used to ensure its safety by being used in clinical screening and diagnostic applications. Non-ionizing radiation, cost-effectiveness, portability, and real-time data collection with display. Despite these advantages, ultrasound imaging has many limitations. Relatively low-quality degradation and imaging contrast caused by noise and speckle image. Variability owing to dependent of operator and hand-held nature during data acquisition and poor image reproducibility in US imaging from different manufacturer's system. [1]

Methods number of images of the liver were used, which were photographed through an ultrasound device for a group of patients between the ages of (20-80) years, through which the state of the liver is determined in the Early diagnosis and treatment of the affected liver to facilitate the determination of the appropriate treatment by the specialist doctor, but The ultrasound device cannot determine the state of the abnormal liver, especially in certain diseases such as cirrhosis and cancer in the early stages. For this reason, we specifically worked in this research to assist the medical staff in diagnosing the state of the liver since the early stages of the disease through the application of the convolution neural network CNN technique by classification pictures of the liver normal liver with a number of 1000 and of the abnormal liver with a number of 1800.

The aim of this research is to use modern techniques in the field of medical examinations with the sonar device and to distinguish images that the device cannot distinguish due to the large number of similarities, noting that this technique was applied first to distinguish between different images of different genders, but in this research, it was used to distinguish between images of the same organ to be examined and to determine its disease state

2- PROPOSED SCHEME

A- Basic Idea

In the present study, a classification framework was suggested for liver by US pictures and employing convolutional neural network (CNN) and time-domain images with numerous features. Because US images are only produced by the magnitude of the echoed radio-frequency signals, the reflections from tumors or large organ boundaries represent the anatomical structure fairly well, despite the fact that CNNs have the advantage of directly abstracting image features from the raw data through the learning procedure, it is challenging to learn some features that are not characterized (wholly or partially) in the raw image. Until now, the strength of any organ's reflected signals, which is typically correlated with the pathology of soft tissue, is barely noticeable in the US image because it is quite modest owing to the nature of diffuse scattering waves and absorption of the propagating ultrasonic. Moreover, due to fewer generalization and over fitting issues, deep neural networks' capacity for self-learning typically declines as training dataset sizes decrease [3].

B- Data Set

The data contained in this research is a sample of image of the liver tissue for the normal and abnormal with ultrasound, derived from 4,000 images, collected from four hospitals and external clinics (Medical City, Yarmouk, Numan, and Carkh) in the city of Baghdad, pictures were taken in the department of Ultrasound and X -rays and were accurately examined by some experienced doctors, but not all of these images have the same resolution and accuracy due to the difference in the quality and efficiency of the ultrasound devices located in the hospitals above where only 2500 images was chosen from among them and after they were processing, they were entered as data in The CNN recruitment program, where we see in Figure (1), image of the liver before processing, and in Figure(2), the liver images, after processing, and Table (I) shows a case of liver images in its normal and sick, which was used in the program. The number of images of the two units is displayed in the table (I), and the American image sample appears for each category (normal and abnormal) in Figure (2).

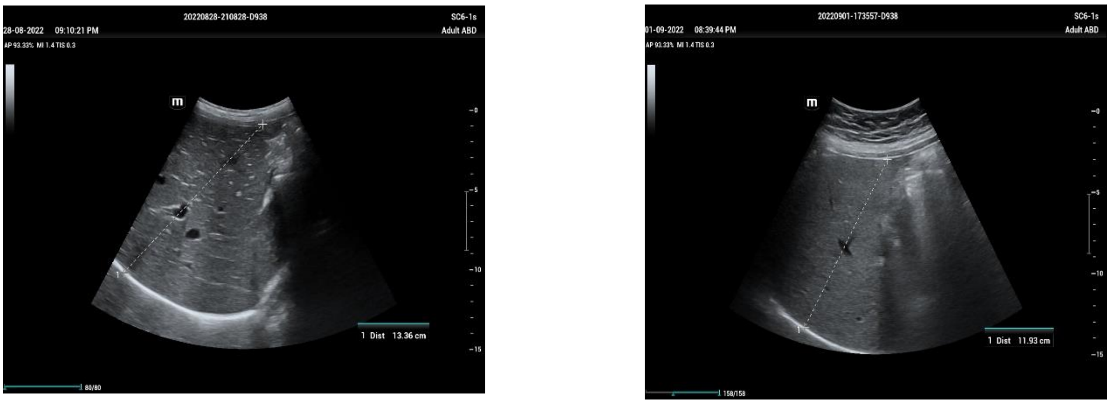
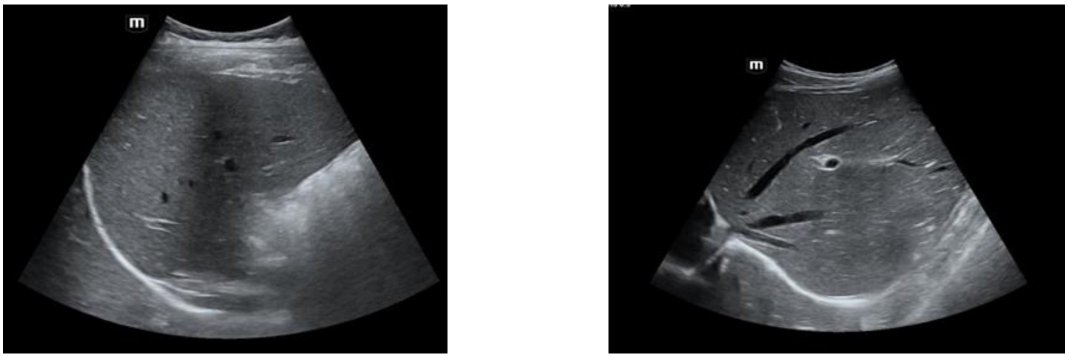


Figure (1): Sample images of the Liver ultrasound dataset, (before processing)

Table (I): two liver US images and the number of images in each class.

class	Number of Image
Normal	1000
Abnormal	1800
total	2800



(a) (b)

Figure (2): Sample images of the Liver ultrasound dataset, (a) Normal, (b) Abnormal (after processing)

C- Network Architecture

The classic CNN uses mode pictures (256 x 256) as training data for the backbone of a network, and then applies the production vector (1x 1000) to the linear layer to produce the final prediction. This modifies all (256 x 256) pixel images used as input data for the backbone network. Two different CNN models were used for each feature-channel image for the backbone networks. The best model was saved when the highest accuracy occurred for the enhancement of performances. Each model of CNN was trained individually with its own images (i.e., Normal and Abnormal Liver Images). [2]
However, since the primary goal of this work is to demonstrate the advantages of classifying liver images, the trials were carried out using a single CNN model for all feature images under identical circumstances., (Figure 3) depicts the general layout of the conventional and proposed CNNs. Where the images that make up the database are processed for this study, this pre-classification step is performed by the neural network and according to the method proposed in (Figure 3). Which contains hidden layers (three convolution layers and three max. pooling layers) and fully connected output layer (Dence function).

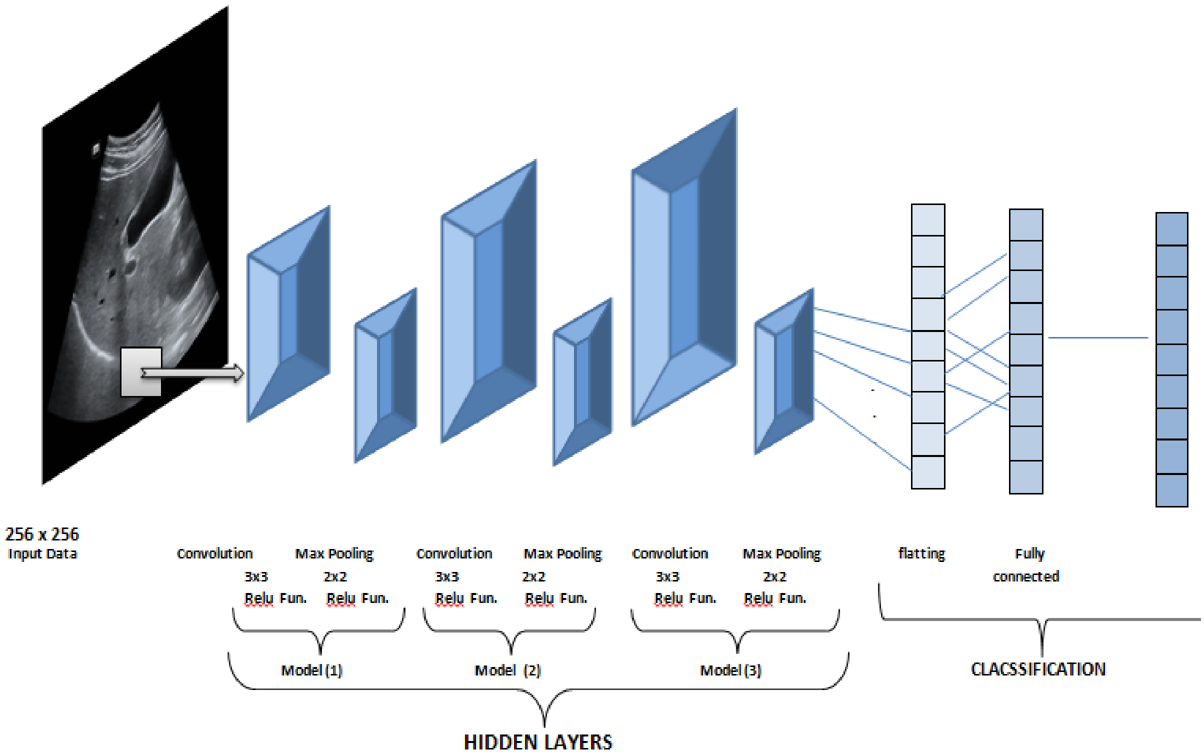


Figure (3): CNN structure

D- Classification:

In the model generation function, the CNN model is described. The convolutional class definition is highlighted, then max-pooling. Convolution2D generates a function that accepts an input and performs convolutions in all possible ways. Layers reappear. A function called max-pooling takes an argument and applies max-pooling to it. A property of completely connected layers is the outcome of the previous max pooling layer. After the maximum pooling and overlapping layers are established. Convolution layers that are dense. Dense build with the output classes parameter set to the desired number (Output Classes Number) which shown in figure (3). The purpose of the loss functions is to evaluate how well the function of networks corresponds with the training scenarios.

It calculates the network's difference (or error) throughout the recognition process. The labels and the prediction probability of the network is an instantiation action to constitute cross-entropies using the sigmoid activation function. The last dense layer doesn't need the activation function due to utilizing the sigmoid procedure together with the loss function of training. During training, the loss calculation function is used, all the layers (convolution, max. pooling and dense) were described in the table (II).

There are 2,800 liver photos in the training file, including 1000 of the healthy liver and 1800 of the diseased liver as shown in table (I). The program separates the files into 32-image groups. The labels and training file features are represented by y and x, respectively, in a neural network input map. The variable of data receives a fresh set of images from the input plan of the neural network at each reiteration of the iteration structure. The training function within the trainer class receives the data as an argument after that. When the network has sorted every image in the training file, the training season is over. Each training file received thirteen epochs (number of training combs = 30), and the test file received 1 epoch. The testing procedure starts at the end of the training stage. The test file comprises 30 images, 15 of which are normal liver status and 15 are abnormal liver status, all interleaved. The separate code selects these images as a batch, and then, similar to the training process, the test file is utilized to make an input chart for the neural network. The set of images that read from the neural network input chart is deposited in the data variable. The data is passed then, as an input to the test function that developed under the sample class, which outputs the error value returned by the network for each batch of the test run. The test result, meanwhile, is the total of the training batch's partial mistakes. The average error in assessing the CNN model is computed following the training process and displayed to the user in the device. Lastly, the CNN model builds (generate model) and reads (generate reader) functions of the training and test files that are done by the Train test function (attributed to train the reader and test the reader, respectively) [5].

Table (II): Architecture of CNN

model	layers	Filter	kernel	Activation function
model	convolution	32	3x3	Relu
1	Max. pooling		2x2	
model	convolution	64	3x3	Relu
2	Max. pooling		2x2	
model	convolution	128	3x3	Relu
3	Max. pooling		2x2	
output	Denese	2	1x1	sigmoid

3- RELATED WORK

The CNN technique, detailed in reference [1], was used to detect mass liver from a 450 × 450 pixels US image. A GPU (Graphics Processing Unit)/CPU (Central Processing Unit) comparison shows that GPU execution acquired a significant benefit on the CPU, roughly quicker 10.6 times from the training and the inspection cases. Dense data requires a lot of computing power during neural network training resources. In view, the entries of the grid are proportional to the number of the pixel in the picture and be equivalent [4,5].

Where the CNN model was designed from three layers of convolution with kernel filter (5x5) and three Max-pooling with (2x2) filter, which is shown in figure (4), produced the details of model.

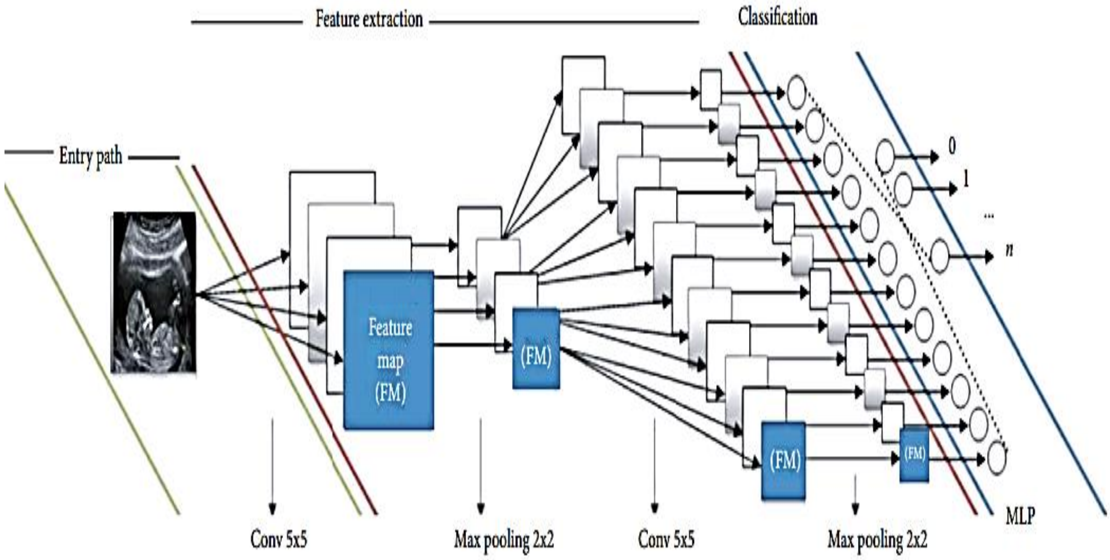


Figure (4): CNN for two stages and different stages [1].

Therefore, CNN technique was used in reference [6] to compare between two sets of images: Firstly, download the images from widely get into websites, the other method by gathering 700 images from the hospital in ultrasound techniques. The quality of ultrasound images (QUI) [7], is critical instruction in the applications of the medical field. Also, it is a significant index for assessing the performance of types of equipment in ultrasound imaging and algorithms of image processing. However, as IQA has traditionally been considered a subjective issue, there are still no recognized quantity criteria for assessing medical image quality, especially in the case of medical ultrasound images. Two CNN models are detailed (IQA-8 & IQA-14). The IQA-8 CNN model is designed from 8- convolution layer and 2-Max-pooling layer as shown in the figure (5). The IQA-14 CNN model is designed from 14-convolution layer with 2-max-pooling layer, the tow model used (3x3) kernel for convolution and (2x2) kernel for max-pooling.

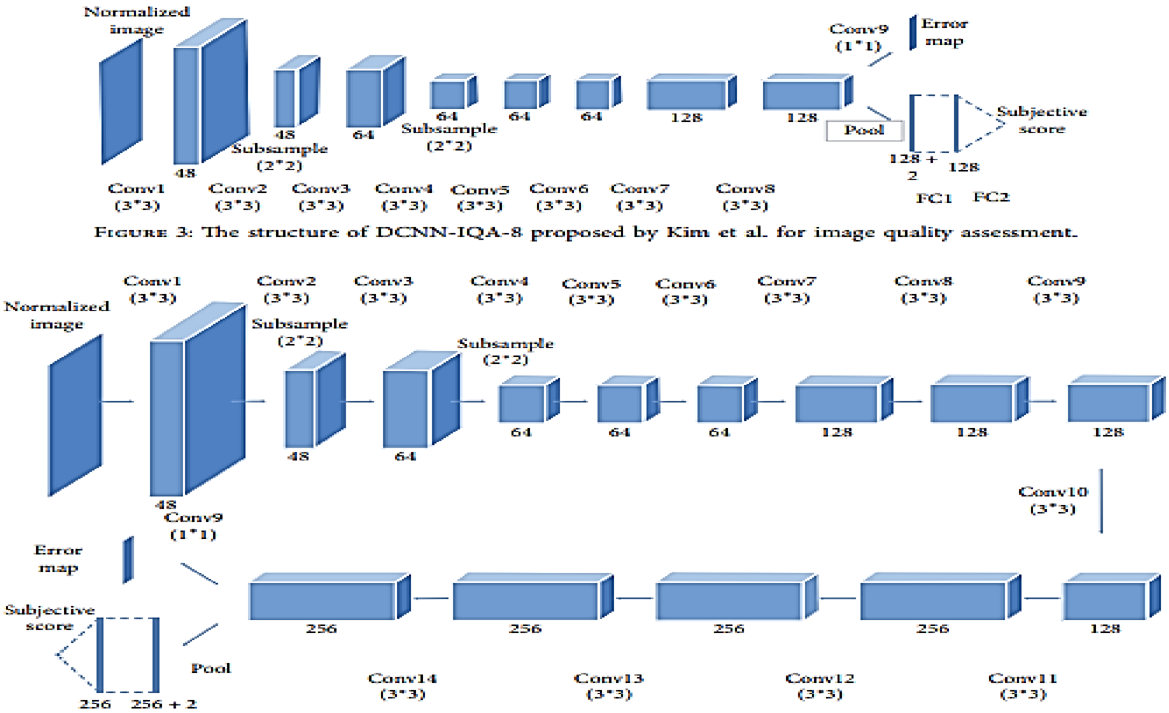


Figure (5): DCNN-IQA-14 structure to assess the quality of ultrasound image [6].

The reference [10] the author used CNN technic precise diagnosis and primary finding of problems in liver. The sorts of differences will be fewer dangerous if noticed and identified steatosis liver primary, but there is found another method for detecting Hepatorenal Index (HI) [11], the ratio of the mean brightness values of the liver and kidney cortex, and the gray-level representation on the matrix method (GLCM) [12] method to offer information on image goodness incorporating distinction, homogeneity, and linearity [13]. At the similar depth, two regions of attention were identified, matching to the liver and kidney rind. This CNN model was designed from 3-convolution layers and 2-max-pooling layers, and three fully connected layers, as shown in the figure (6).

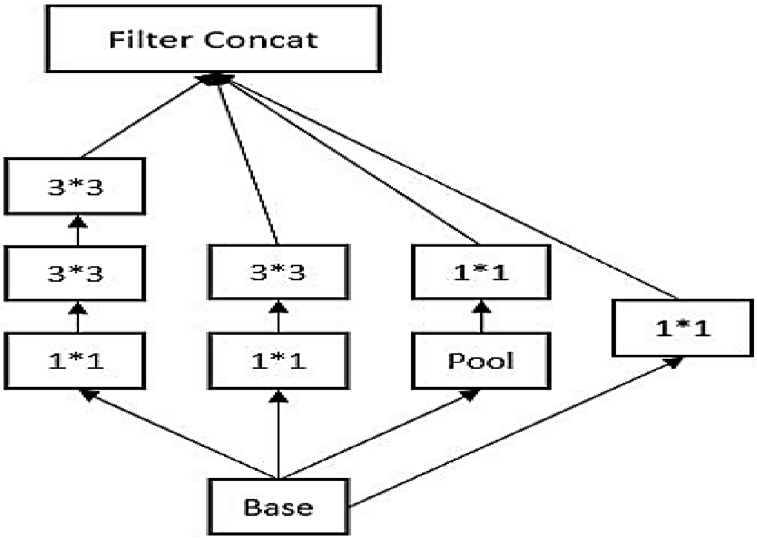


Figure (6): building block representing smart factorization [10].

The reference [14] studied the classification of chronic liver disease which has been a vast medical onus. It generally includes B and C hepatitis, disease of fatty liver, disease of the liver autoimmune, thereby, hereditary and metabolic disease of liver, etc. The paper's main work is focused on the intelligence fibrosis classification in CLD patients [15]. Firstly, a convolutional neural network mode l (CNN) is built to perform categorization tasks over images. A radiomics style [16] is also implemented to extract radiomics merits from images and build parametric model. After then a machine learning classifier is used to categorize the liver fibrosis. This CNN model was designed from sixteen convolution layers with kernel filter (3x3) & (5x5) without using max-pooling layers, as shown in the figure (7) [17].

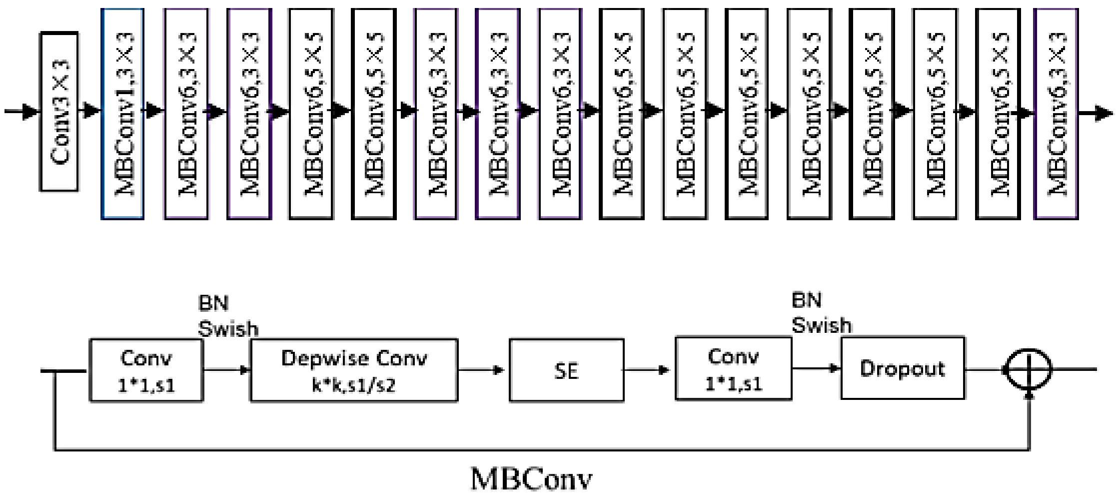


Figure (7): Efficient Net model structure [14].

The CNN technique, detailed in the reference [18] proposed a nonalcoholic full of fat liver disease categorization from US data, since corresponding patients are at an increased risk for the development of cirrhosis and hepatocellular carcinoma (HCC). In spite of the medical imaging nature, the amount of data for the medical image is limited. Thereby, transfer learning in many times used to override the sets of small training for processing the neural network. The network is primary trained using the image net dataset consisting of normal images. The dataset of liver ultrasound images by matching the small dataset through network learning was augmented for the trained network [20] in study. This dataset is then further augmented by mirroring, collecting, and rotating to make better robustness of neural networks.

In the present work [18], the researchers designed new multi-features of CNN architecture by integrating features extracted from ultrasound image data. Merging feature maps can achieve extension and effect of complementary features between different features. Where different fusion structures have been achieved to improve prediction.

The multi scale analysis was integrated into the CNN architecture of this research by using additional convolutional layers with different kernel size, which leads to extracting more relevant elements and information from the baseline feature maps, and thus the proposed approach was evaluated on ultrasound scans taken from 550 people with Comparison with modern methods.

In this CNN model, detailed in figure (8), each block was designed from six convolution layers and one Ave.-pooling layers with filters sizes of (3x3), (2x2), for block1; (5x5), (3x3) for block2; and (7x7), (5x5) for block 3 [21].

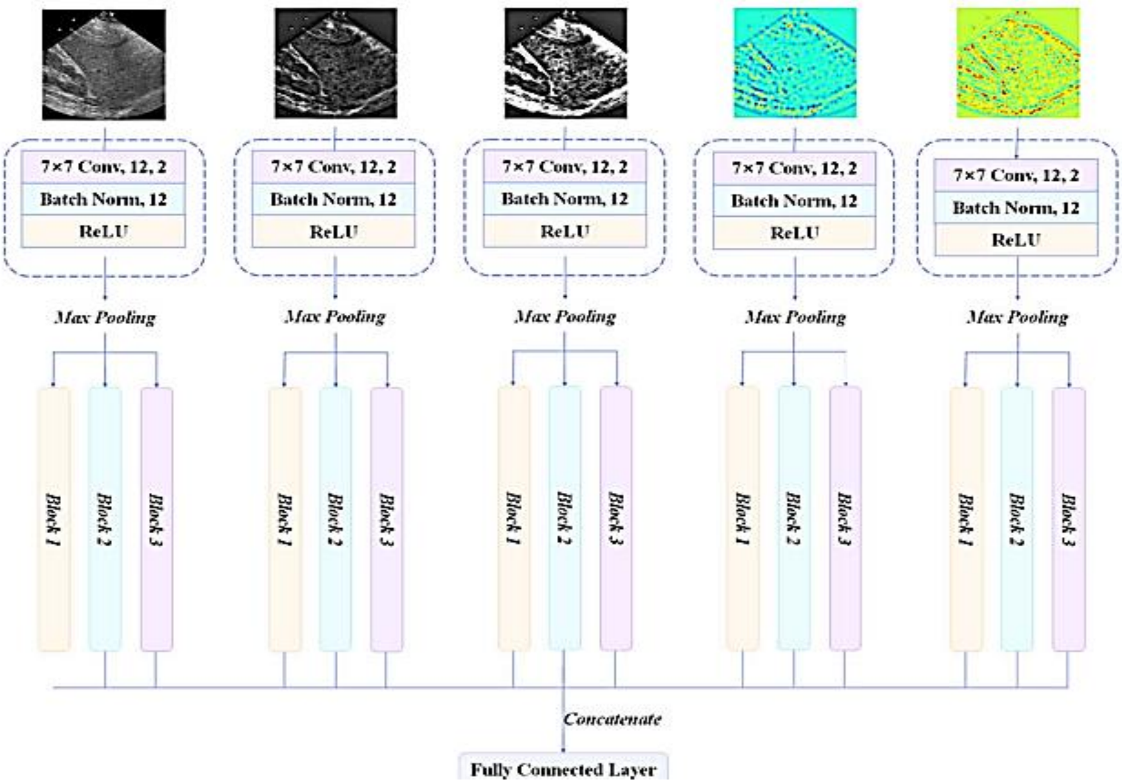


Figure (8): The CNN architectures of every convolutional layer have three parameters: kernel size, depth, and stride [18].

Therefore, the CNN technique was used in reference [22] of the author categorizing liver cirrhosis grounded on data from images of ultrasound used in convolutional neural networks (CNNs) are broadly used in medical imaging. Recent research addresses liver disease detected in ultrasound images. It takes a deep learning approach and uses a combination of handcrafted functions and classical classifiers. Cirrhosis is the greatest dangerous liver disease. So, it is difficult to gather an enough amount of data. Consequently, the limitations of obtainable cirrhosis data add to the difficulty of the pattern recognition problem. Therefore, the average error rate may be higher for a finite dataset than for another type of dataset.

Figure (9) shows the CNN model was designed from two models each model contains from convolution layers, and Max pooling layers, with kernel filter (3x3) and (2x2) respectively.

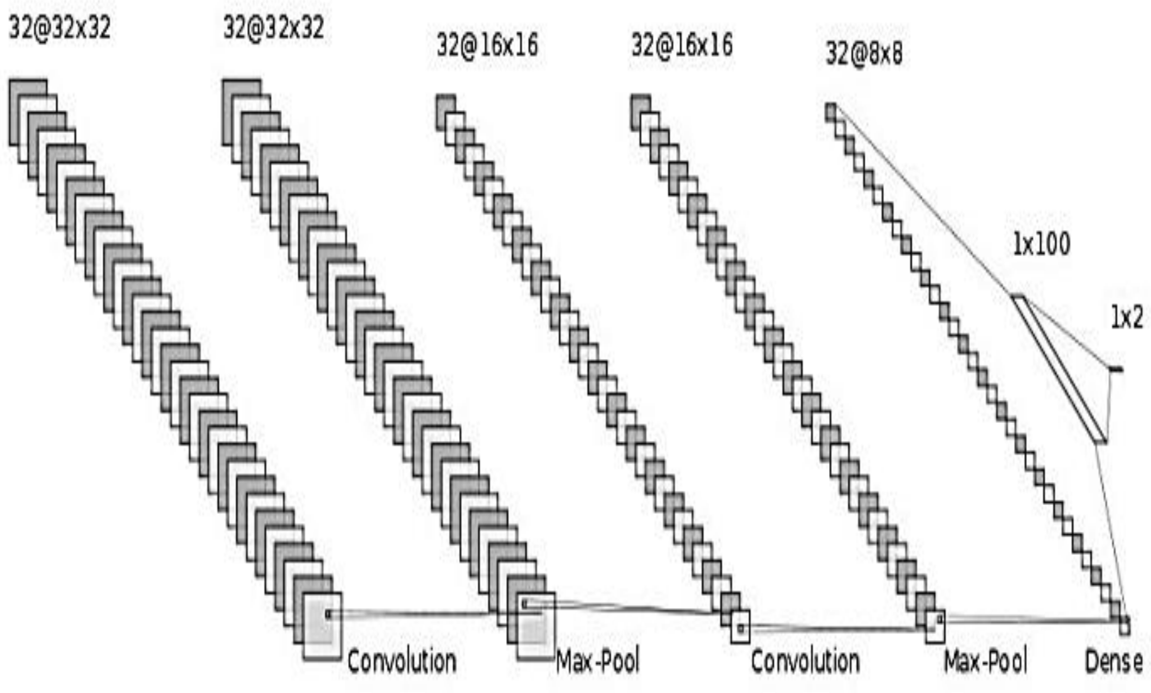


Figure (9): CNN structure [22].

The reference [25] the author used CNN technic a process that presented the assessment of liver healthy out of ultrasound imaging. Because it is non-invasive and practical thanks to the classification of the liver ultrasound standard planes, it is widely utilized in clinical liver assessment. On the other hand, the ultrasound machine's imaging principal results in undesired image qualities including shadows and speckle noise, which are inherent to the image. Methods evaluated in this work were mainly about traditional machine learning and deep learning. Figure (10) shows the selected CNN designed from 5-models: model (1&2) contains 2-convolution and 1-maxpooling layer, but the last three models contains 3-convolution and 1-maxpooling layer and three fully connected layers with kernel filter (3x3), (2x2), (1x1) respectively.

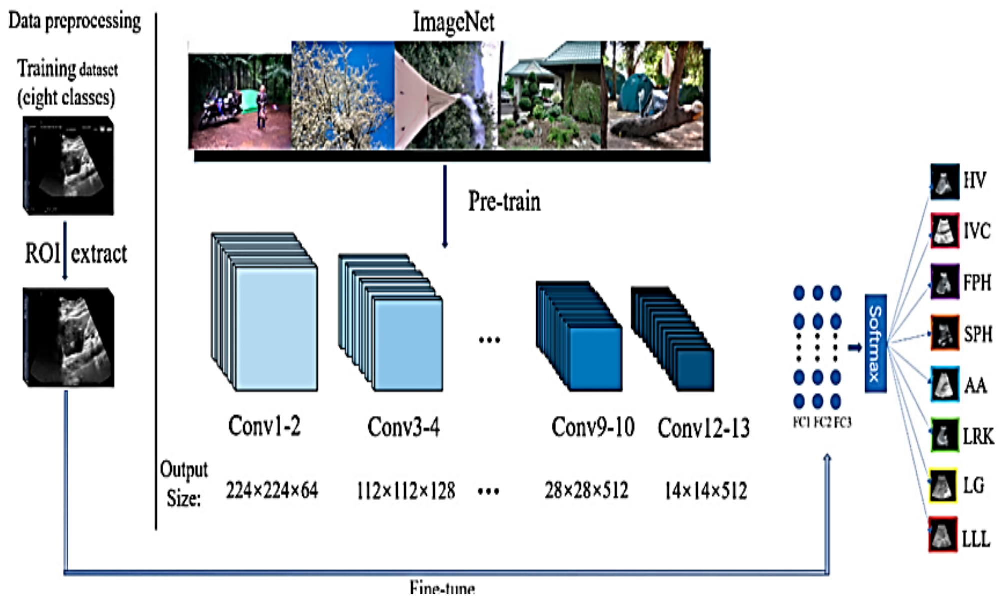


Figure (10): CNN structure [25].

So that the reference [28], the authors used a set of images classification of fatty liver disease (low-grade fatty liver, moderate grade fatty liver, and severe fatty liver) in its simple, medium and deep three degrees in various sizes of images through the use of CNN technology to classify fatty liver cases and indicate the extent of the effect of image size in extracting the accuracy of the results, performed utilizing the image spots with the diverse size as

28 × 28, 35 × 35, 40 × 40, and 55 × 55 pixels. it can be seen that there is not much difference between the different sizes of Images. The size of 55 × 55 pixels might have higher

exactness in the early step of training, but its accurateness is decreased with the number of iterations increases. This is due to the size of the image will be too large, However, Figure (11) shows the selected CNN designed from 3-models: model (1&2) contains 2-convolution and 1-maxpooling layer, fully connected layers with kernel filter (3x3), (2x2), (1x1) respectively. The filter size of 3×3 has a faster speed of convergence, and its calculation of parameter amount is less than 5×5 and 7×7. Thereby, the size of the final filter is 3×3 [28].

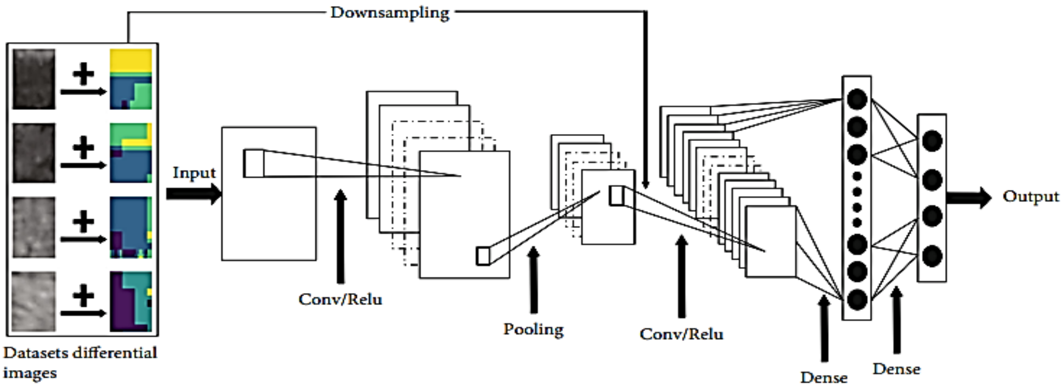


Figure (11): The flowchart of the proposed CNN architecture [28].

4- COMPARATIVE OF THE AUTHORS WORK TO THE RELATED WORK

Works proposed in [1] showed that applying the CNN technology using the GPU takes less time than applying it to the CPU, and this encourages programmers to use more data to get better results. The design of the model [1] was based on Convolution and Max-pooling layers leading to an accuracy rate of 91%.

Therefore, it is possible to construct a graph to observe the network's learning for each k of the k-fold technique run. For the proposed CNN models, having one, two, and three convolutive layers followed by max-pooling, an average accuracy of 50%, 65%, 83.5%, and 85%, respectively, was reached. As for the test subsets, the accuracies correspond to 58%, 66.6%, 75%, and 91% Figure (12) explains this difference in accuracy by comparing the average errors and the errors of the test subset for each number of layers.

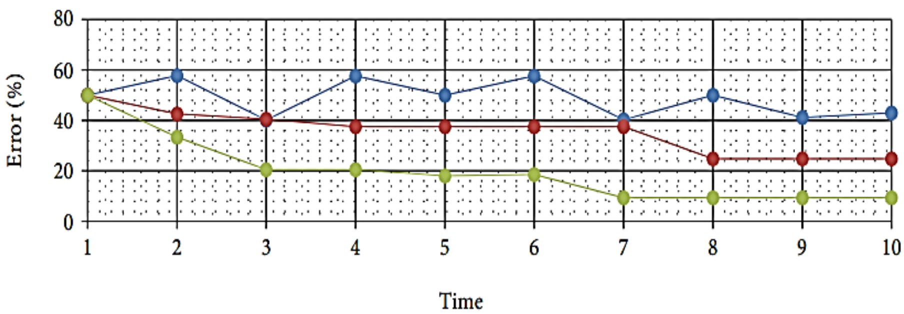


Figure (12): The neural networks learning graph proposed for the execution of K = 9 [1].

But regarding for the research proposed in [6], it relied on the impact of database quality on extracting the best results. The US images achieved better results if they had a high resolution, the model design relied on a double number of convolutions and one layer of max-pooling for each model, but when increasing the number of convolutions, the implementation of the program is delayed because increasing the number of nodes used in the program as shown in figure (13).

All results indicate that learning to evaluate normal image quality has important improvement in the ending effect suitable for quality of ultrasound image valuation. Improve the network performance to a certain extent can be solved by Transfer learning for the network overtraining problem caused by the limited amount of ultrasound images.

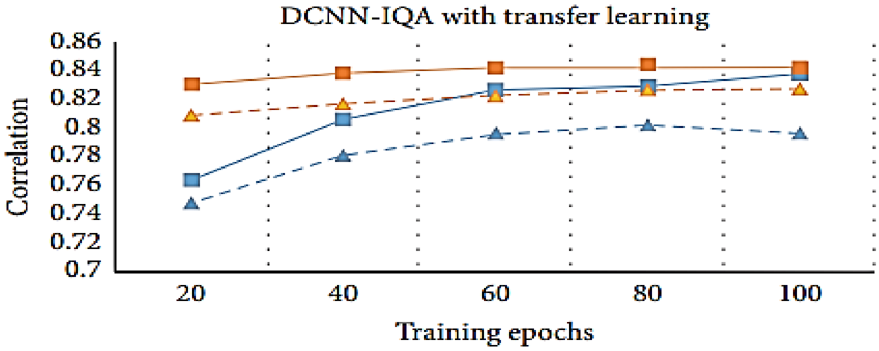


Figure (13): the effect of convolutional layers in DCNN-IQA [6].

Results obtained with [10] using a usual model, based on two convolution layers followed by the Max-pooling layer, show a very high accuracy rate reaching 98%.

Fig. (14) represents the training progress of the model. Where the loss and accurateness are computed on training and authentication with its interpretation is based on how well the model is carrying out on these two datasets. From the accurateness plot, it is showed that the increased trend continual up to 250 epochs, where it reached the maximum accurateness.

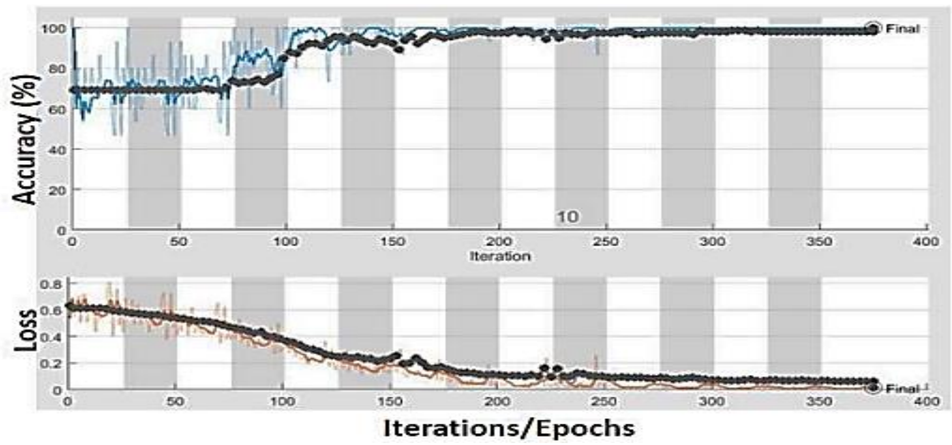


Figure (14): Accuracy and loss curve of the model though training on both train, authentication data. The model has not over-learned on the training dataset as it observed comparable results on both datasets [10].

With 84% of accuracy rate obtained in [14], the importance of sustaining the max-pooling layer in the design of the model is highlighted.

There are (117) patients in the F1 stage accounting for (62.6%) of total patients and 13 (7.0%), 23 (12.3%), 21 (11.2%), 13 (7.0%) for F0, F2, F3, F4 stages, respectively.

It can clear from Table (2), that the classification results of liver fibrosis utilizing the CNN model are well indicating that. F4 indicates for the cirrhosis group, advanced fibrosis group (≥F3), and important fibrosis group (≥F2), the classification accurateness of the test cohorts gotten above 0.8 with the sensitivity and specificity above 0.70 and the AUC value directly above 0.78. The ROCs of the three groups are shown in Figure (15). Among them are, the advancing fibrosis group (≥F3) has a lower value of AUC, which might be because that the feature variances between the F2 and F3 stages of the liver fibrosis isn't clear and less distinct; it may also be because the unfair data spreading of smaller amount in F3 and F4, though larger amount in F1.

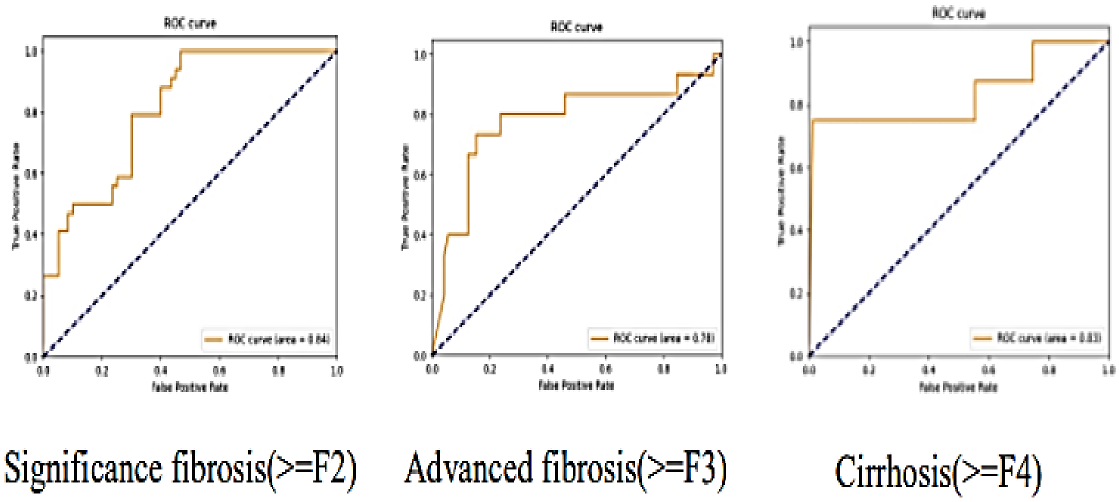


Figure (15): ROC curve of CNN model for different liver fibrosis stages [14]

An accuracy rate of 97% is obtained in [18] relied in designing the model on the formation of three blocks, each block consisting of six layers of convolution with one layer of Ave.- pooling, not Max-pooling, Algorithm proposed in [22] is almost similar to the design of the model in [10], was show in figure (16).
Through this study, we find that the researcher used a new path in relying on CNN to improve classification of American data. Image enhancement based on local phase and feature illustration can highlight liver tissue features by providing significant information to the image to improve data classification performance in CNN. The qualitative results appear in the use of multiple features in a multi-scale CNN, which leads to improving the performance of liver classification in terms of accuracy. Fast radiographic symmetry is characterized by medium fusion and late fusion, which outperforms early fusion, which indicates a strong correlation between the features of the different images obtained. After convolution operations, the researcher explains that combining features is valuable for traditional classification methods.
In the quantitative evaluation, the researchers found that in most cases, the normal class measures were lower than the abnormal class, whether by typical methods or by the methods proposed by the researchers, which rely on classifiers to classify normal livers as low. Therefore, it can be said that the benefit of a smaller number of normal liver data in the examined data set is a possible reason for these low results. However, compared to that, it showed superior results over traditional methods in the case of classifying the ordinary category.

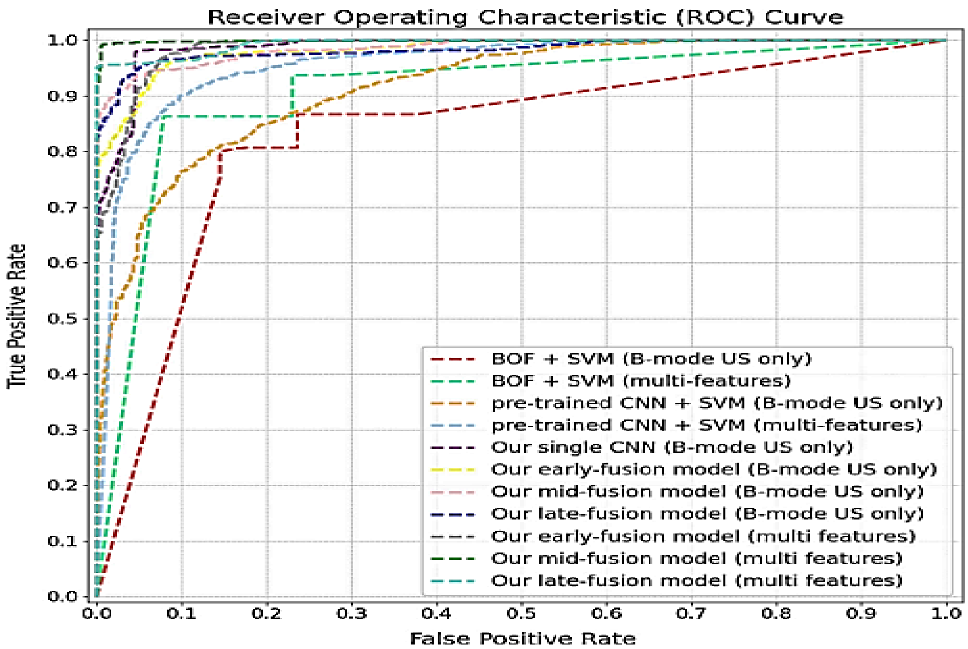


Figure (16): The ROC curve for every method. AUC value is exhibited for every investigated architecture. Mid-fusion model with multi-features input gains the highest AUC value [18].

The Authors in reference [25] in many training data, a deep learning model can automatically access relevant features. Usually, the performance result of methods based on deep learning is better than methods based on traditional machine learning techniques, because ultrasound images are difficult to design, into the field of ultrasound image processing. Manually, efficient features and on the other hand deep learning models are hard to put on into ultrasound image data, due to the limited obtainability of big ultrasound images. Concerning this problem, there are two ways to mitigate it. Methods can be divided into two sorts:

- The first could increase the size of the data via data augmentation.
- The second is that traditional data augmentation operations should be geometric transformations, such as flipping, shearing, etc., as well as color transformations. It has been proven to be an active way to augment data by superimposing images.

Moreover, the other solution is the transfer learning layer which decreases the quantity of data wanted to train the network by transferring the knowledge of the large dataset to the medical image. So, the researchers created a 13-layer CNN model. In this model, choosing a small size kernel to capture the characteristic features of the inner class. Moreover, the transfer learning method was applied to carry out the model training process for the results, which avoided over-fitting the model as the largest scale can be obtained, as the result expresses that the proposed methods have the ability to accomplish this task well.

However, the [25] was designed by increasing the number of models, but in the same order in the use of layers, and the accuracy rate was less, reaching 92%, the authors work using data set (ultrasound image) was designed from three models each model consist of convolution and max. prolong layers, the accuracy rate was reached 99% as Shawn in Figure (17).

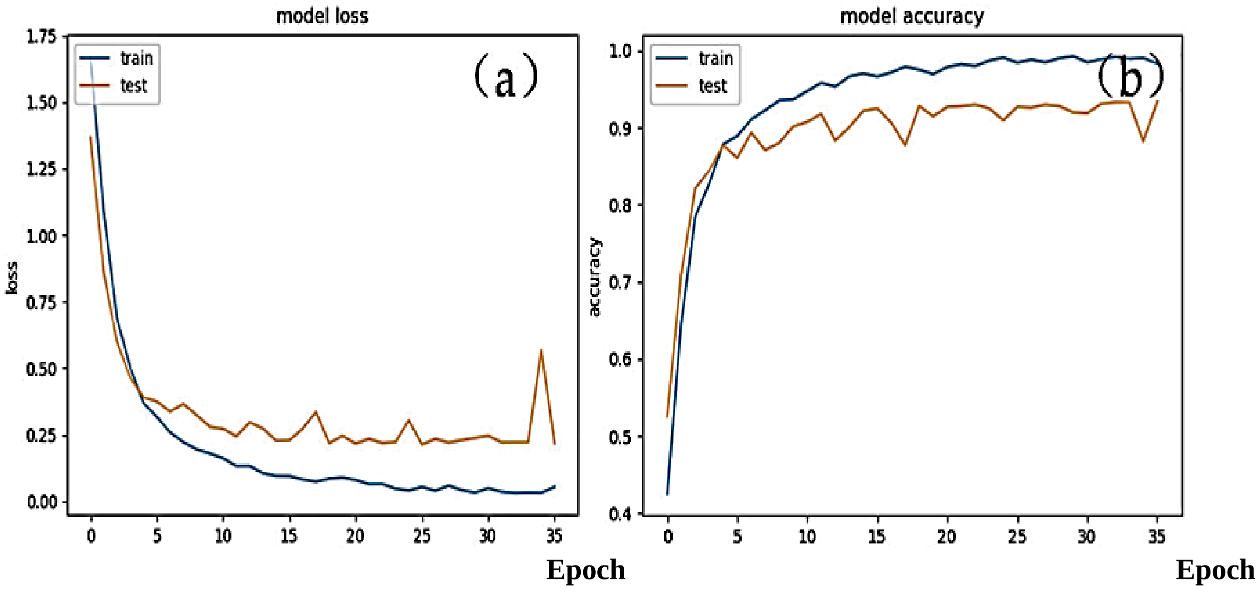


Figure (17): The loss cure and accurateness curve of fine-tuning of the planned CNN model: (a) Authentication loss curve, and (b) training curve for VGG16 that fine-tuning all network layers with Image Net pre-trained models [25].

In other study was used in reference [22], the researchers focus on ultrasound imaging of the liver, where this data includes 12 patients with liver cirrhosis and 8 normal people, and each person has five ultrasound images, where they focused on classifying the fibrous areas of the liver from the ultrasound images, and then 200 images of the liver of normal subjects and 300 images of cirrhosis were collected. Each image has a size of 32 x 32 pixels. The gray level was 8 bits. Thus, the values ranging from 0 to 255. This is a typical problem of two categories, normal or cirrhotic. From this shape, it appears hard to classify the liver as typical or cirrhotic if one is not a physician due to of the noisy ultrasound images. Where the researchers relied on improvement methods in image classification by adjusting the image contrast, then improving the image excellence, which leads to improving the generalization capability of CNN. So, since the planned method improves image quality for image pre-processing, so these image correction methods should be considered for future cirrhosis classification and also validation processing of the proposed method for another dataset in the work. Moreover, the structure of CNNs should be considered. And also considering further improvement in the classification of cirrhosis. [24]

The last research [28] The researchers relied on the size of the image taken from the ultrasound device to obtain the best results to determine the fatty liver diseases using the CNN technique (low-grade fatty liver, modest grade fatty liver, and severe fatty liver), and the highest value of accuracy was in the largest image size, and this leads us to the fact that a good image must be of high quality and resolution To obtain the best results in determining liver diseases.
It can note that the researchers in this research discussed the impact of many reasons that affect the accuracy of classification in determining the results, including the number of convolutional layers and the use of more than one type of filters and their impact on the results as show in figure (18).

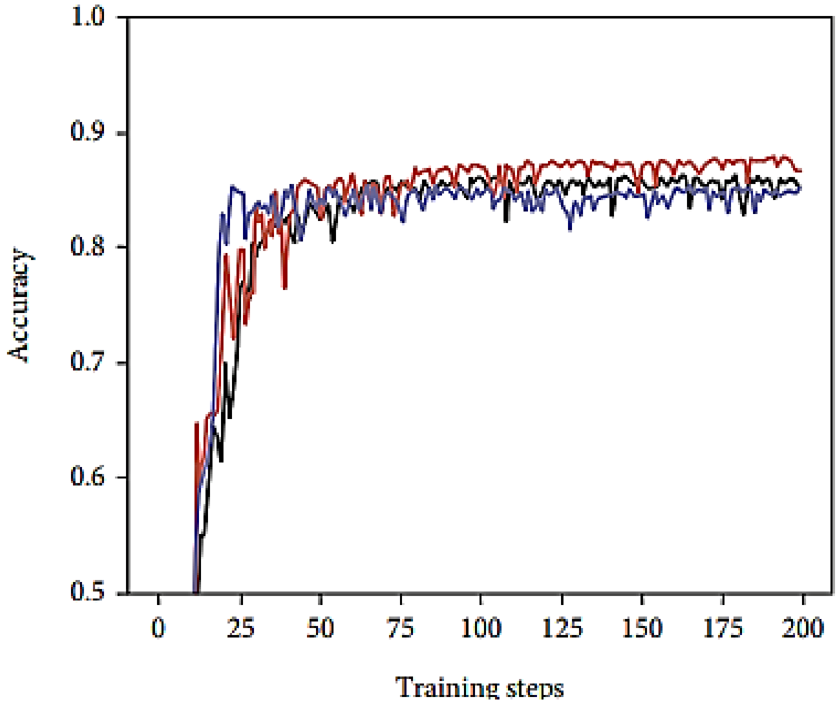


Figure (18): Comparison of accurateness on liver ultrasonic images through training for CNNs with diverse structure components [28].

Here are all these details more accurately which is describe in the section of related work are surmised in Table (IV).

5- RESULTS & DISCUSSION

To determine the convolutional window's size, the kernel sizes filter (3x3) was investigated. The pooling function minimizes the network's data dimensionality. There are methods that use three convolution layers, followed by max-pooling and a single displacement step. The promotion of agility in training and the creation of spatial invariance are both benefits of this reduction. The next layer's input was cut in half by using the max-pooling function with a kernel size filter set to the (2x2) window. The filter size 3x3 window permits the addition of more convolutional layers, these layers were followed by max-pooling on the input image in addition to lowering the average classification error. The images are just 256 x 256 pixels in size, and the convolutional and max-pooling techniques result in significant reductions. Hence, their physical capacity must be considered. A 3x3 window of convolutional with a one-step displacement was then applied next to that.

Before that, the images were used as input for the classificatory, and the number of the layers applied was modified after defining max-pooling windows and the convolutional. For each quantity of convolutional layers, the training and testing procedure using the technique was repeated, therefore, they followed by max-pooling on the CPU.
The params number (Conv2D) as input (448) neurons and output (Normal or Abnormal) neurons, totaling (8389120), was produced by the model (CNN) using max-pooling and only three convolutional layers. The reason for this case that the image when input has a size (256x256x16) pixels, and the conclusion for the first convolution layer, a reduction becomes to (128x128x64) pixels where acts (9280) as the input for the max-pooling, where the locative reduction it produces an image in size of pixels (64x64x16). The max-pooling

function output is fed as input into the neural network. The model (CNN) has (9232) input params the next convolutional layer's output is (32x 32x16) pixels, and its parameters are now the (64 x 64x16) pixels that were the prior model's input to the neural network. The pixels (32x32) are supplied to the max pooling function similarly to the previous model. The CNN with three layers of convolutional and max-pooling follows the similar procedure as the earlier networks. An average accuracy was attained for the proposed models of CNN with one, two, and three convolutional layers followed by max-pooling process withal results obtained in the figure (19).

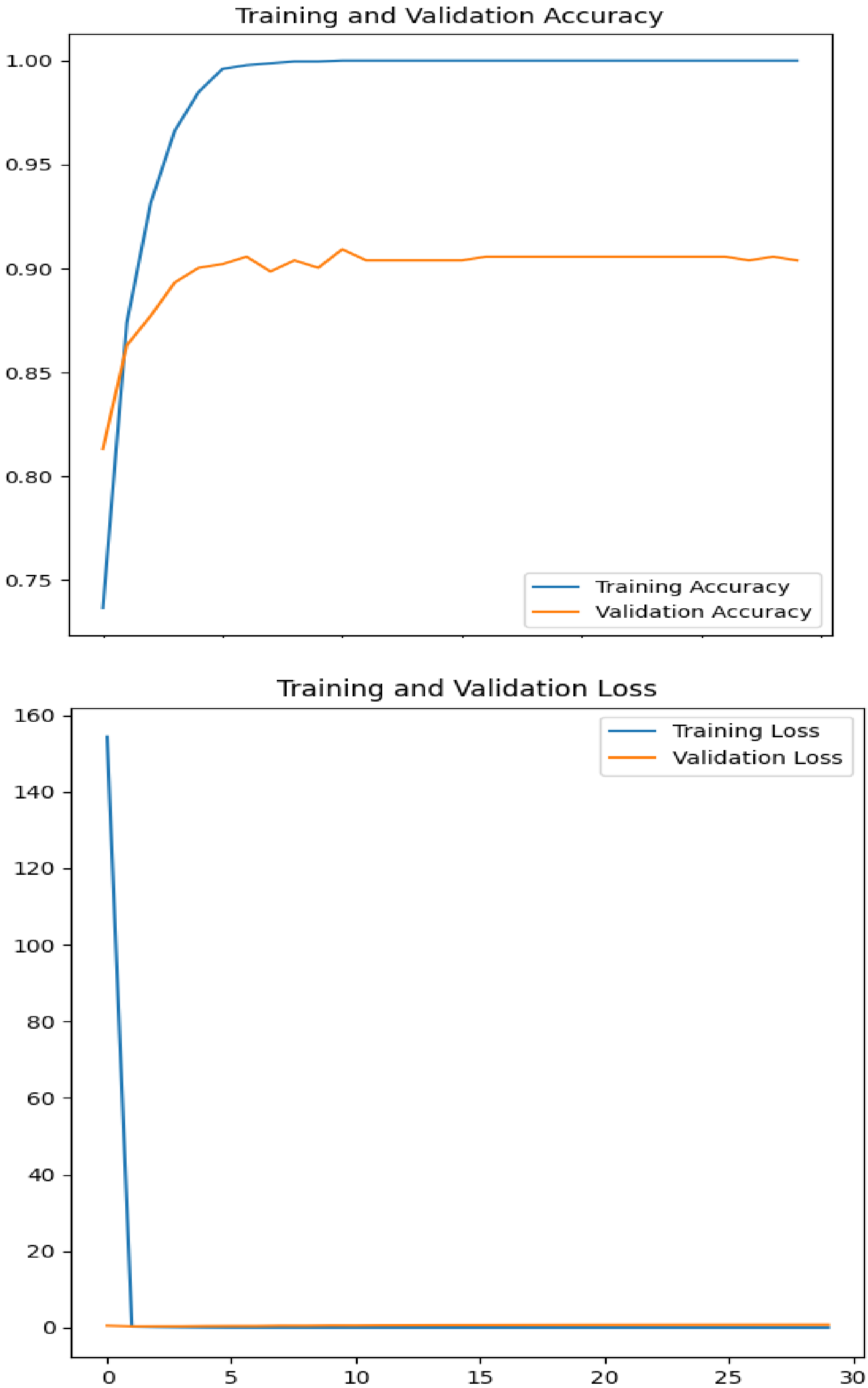


Figure (19): Accuracy and Losses

Table (IV): Comparative of The Authors Work to The Related Work

Year	Author	Aim	Dataset	Model	Building of Model	No. of Filter	Kernel filter type	Activation function	Performance ACC
2022	Lamia Alhazmi and all	using computer in tow way (CPU & GPU) then comparative between them about speed through results of program.	Training file was 108 photos data (54 for positive &54 for negative) *Test file comprises Photos of 12 (six were positive and six were negative)	Model 1 450x450 Model 2 150x150 Model 3 75 x75	Convolutional	32 64 128	5x5	Relu	91%
					Max-pooling	32 32 128	2x2 5x5		
				Out put	Dense		1x1	Softmax	
2021	Siyuan Zhang, Yifan Wang and all	Compare two sets of data (The samples of ultrasound images in this paper come from two ways. Firstly, downloading the images from public websites, and another way is by gathering the images of ultrasound from the Hospital were estimated by 700)	Data image 478 (60% of training data, 20% was validated data, and 20% of testing data) 256x256 pixel	IQA-8	Cov.1-8	48 64 128	3x3	Relu	83%
					Maxp1-2	48 64	2x2		
				IQA-14	Cov.1-14	48 64	3x3		
					Maxp1	48 64	2x2		
				Output	Dense		1x1	Softmax	
2022	Umar Farooq Mohammad and all	early recognition and diagnosis of the liver problems. These sorts of anomalies will be less dangerous if diagnosed and detected steatosis liver primary	dataset consisted of 550 images, 434x636 pixel 75% of data was utilized to train the model for the organization mission and 25% remaining of data were utilized for inspecting the model.	3.convolution layers 2- max-pooling layers 3- fully connected layers	Cov.1,2,3		3x3	Relu	98%
					Maxp.1,2,3		2x2		
				Output	Dense		1x1	Softmax	
2021	Yumeng Zhang and all	can study the classification of chronic liver disease regarded as a massive medical burden. It usually includes hepatitis B and C, the disease of fatty liver, autoimmune liver disease, while hereditary liver disease and metabolic, etc.	Data set 187 with 224x224 resolution 60% training 20% validation 20% testing.	Conv. 16 layers MB Conv. Module	Conv.1,2,3	6	3x3	Relu	84 %
					Conv. 4,5	6	5x5		
					Conv. 6,7,8	6	3x3		
					Conv. 9-15	6	5x5		
					Conv.	6	3x3		
				Output	Dense		1x1	softmax	
				Output	Dense	256	1x1	Sigmoid	

Year	Author	Aim	Dataset	Model	Building of Model	No. of Filter	Kernel filter type	Activation function	Perfor-mance ACC
2021	Hui Che and all	study of disease for nonalcoholic fatty liver that classified in US data because Some patients with nonalcoholic fatty liver disease are also at an increased risk for the development of cirrhosis and hepatocellular carcinoma (HCC), Early diagnosis, improved treatment.	Data set 550 With 512x512 60% of resolution training, 10% of validation, and 30% of testing dataset.	Hidden layer	convolution	64	3x3	Relu	97 %
						128	5x5		
						256	7x7		
					Ave.pooling	256	2x2		
							3x3		
							5x5		
				output	Dense		1x1	Softmax	
2022	Yoshihir Mitani and all	the liver cirrhosis was classified from the ultrasound images data.	Data set total: as 200 of normal and 300 cirrhosis images. 60% training, 20% validation & 20% testing 32 by 32 pixels.	Hidden layer	convolution	32	3x3	Relu	95%
						16			
					Max-pooling	16	2x2		
				output	Dense	8	1x1	Softmax	
2021	Jiaxiang Wu and all	liver health assessment through ultrasound imaging is utilized worldwide in the examination of clinical liver due to its practicability and non-invasive classification of the liver ultrasound standard plans.	Data set 8 224×224 80% training 20% validation.	Hidden layer	convolution	64	3x3	Relu	92%
						128			
						256			
						512			
					Max-pooling	64	2x2		
						128			
						256			
						512			
				output	Dense	8	1x1	Softmax	
2022	Haijiang Zhu and all	propose a classification method through CNN with the differential images based on pixel-level features for the normal liver, low-grade fatty liver, moderate grade fatty liver, and severe fatty liver.	Data set 32 with 28x28 35x35 40x40 55x55 resolution.	Hidden layer	Conv. Max.pooling	32 64 198 250	3x3	Relu	92 %
				output	Dense		1x1	Softmax	

6- CONCLUSIONS

Through the implementation of the CNN technic, the data was used with a total of (750) images at the beginning without processing of the images as shown in Figure (1) and the average accuracy was 40% and after processing as it is evident in Figure (2) with the same number of data that was done Its use in the implementation of the program was observed that there is an increase in the average accuracy by 60% and after gradually increasing with increasing the number of data to (2500), we notice an increase in the average accuracy gradually in conclusion to 98%, and from this it turns out that the image with a high resolution affects a positive impact on obtaining the results of the program, but it is It is not sufficient in the CNN technic, where there is an important factor with a positive and strong impact, which is the increase in the number of data used in the system. The higher the number of data, the higher the obtaining of high -quality results as shown in figure (19).

The model (CNN) was able to classify liver status of liver ultrasound images with an average accuracy of 99% for all images examined, and this model (CNN) can be expanded to characterize with classify normal and abnormal liver status. the liver condition can be determined with the help of increasing the number of images in the database and then determining every type of liver case, that has been identified through the images. Then can be kept by the set of images for the healthy liver with its labeled to avoid a false identification with database growth and prevent the increase in the training and testing time of CNN, which necessitates the use of an environment with high processing power. After completing the training and testing, a graphical interface can be advanced that permits users to submit liver ultrasounds images for analysis, the result in a diagnostic aid can be utilized for educational purposes and to collaborate with medical students for training and qualifying to achieve this way. Through the implementation of this technique, CNN, we can distinguish and detect other liver diseases, such as: Liver cancer (similarly recognized as hepatocellular carcinoma), cholangiocarcinoma (that affecting the bile ducts within the liver), hemangiosarcoma (a tumor of the blood vessels), and hepatoblastoma (that affecting children) were all examples of lumps that originate in the liver. Based on these researches' observations, we can conclude that the CNN technology is a very good technique in the early detection of diseases and determining the type of disease. Effectively, by entering the images taken with the ultrasound device, convincing results could be obtained through the application of the adequate CNN program designed for this purpose. The present work sheds light on this modern technology for the purpose of using it in detecting diseases that affect an important organ in the human body, which is the liver, and through the authors research, which is still working on obtaining the best results and comparing them with the results obtained from a group of hospitals, which are the Medical City and Yarmouk And Al-Numan and Al-Karkh are among the best qualified doctors in this field, where the percentage of results was 98%. Accuracy in obtaining these results depends on choosing high-resolution images, where the program can correctly store the characteristics of each disease case and then compare with the images. The other used by the program for examination and diagnosis of disease.

7- FUTURE WORK

- Complete and develop the program results.
- Compare the result obtained with the ultrasound results taken by the clinical user.
- working on another research in the same branch but used data image of Kidney.
- Obtained the difference between CNN, ANN & RNN technic.

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