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An Improved Liver Diseases Detection and Classification Using Deep learning algorithms

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Abstract

Liver disease is one of the most common human diseases that is difficult to detect early. Advances in information technology, particularly artificial intelligence (AI), advanced neural networks, and the availability of computed tomography (CT), ultrasound, and MRI images, have contributed to the development of models that can be used to detect and classify liver diseases. Our proposed study will focus on the importance of preprocessing and feature extraction to achieve high diagnostic accuracy. This involves identifying regions of interest (ROIs) and segmenting the liver. We identify the liver's center point from the images and feed it into a convolutional neural network (CNN). The CNN is trained on this part of the image. The remaining part of the image is then fed into the CNN, and the CNN is trained on this part. Two networks, one for each segment, are used. The features from both segments are then combined to provide a clear visualization of the network. Therefore, image segmentation to identify the region of interest is important for improving classification accuracy and more effective disease diagnosis. Our proposed study used various advanced neural network models and achieved good results that outperformed previous studies. The ResNet50 model achieved the highest accuracy of 97.94%, the ResNet101 model achieved an accuracy of 97.42%, and the custom convolutional neural network achieved an accuracy of 92.11%. Through these results, we note significant progress in the classification of liver diseases and the potential of the models used in detecting and classifying liver diseases. They can be used by doctors to assist them in their workflow to diagnose liver diseases and integrate these models.

Keywords: liver disease, CNN, ResNet50, ResNet101, Vgg16, ROI.

1. Introduction

Liver diseases are considered serious diseases that are difficult to identify, detect, and diagnose early. Liver cancer is one of the types of liver diseases that lead to death. There are two types of liver cancer, which quickly affect the liver and lead to the formation of benign and malignant tumors. Malignant tumors, if not diagnosed immediately and early, spread throughout the human body and cannot be controlled except through surgical removal [1]. The other type, benign tumors, are among the most widespread and common tumors, cannot spread, and generally do not affect the liver [2]. Liver tumors are among the most widespread diseases that affect people's lives and lead to death. Therefore, they must be diagnosed as quickly as possible to preserve lives and reduce deaths. With the recent development of information technology and artificial intelligence and the availability of deep learning technologies, specifically advanced convolutional neural networks, which have contributed to disease diagnosis, and given the availability of medical imaging images such as resonance imaging, computed tomography, and ultrasound, they have greatly assisted in the detection and classification of liver diseases.

In addition, using image segmentation techniques and manual identification of regions of interest by diagnosticians or traditional methods has increased the accuracy of liver disease diagnosis [3-4]. sometimes cancer develops in the liver itself or other organs. The most common types of tumors are bile duct cancer and hepatocellular carcinoma, and the cause may be either a virus or an alcoholic infection, which causes hepatitis. There are several types and categories of hepatitis A, B, and C, with hepatitis accounting for 75% of all liver cancers [5]. Therefore, models are needed to diagnose liver disease. Given the availability of imaging technologies, as mentioned previously, they provide a clear view of liver damage. Ultrasound images can be used to identify cases of liver cirrhosis, which is considered a cause of liver cancer. Therefore, early diagnosis and treatment of liver cirrhosis are essential [6]. These studies aim to improve and increase classification accuracy and reduce errors

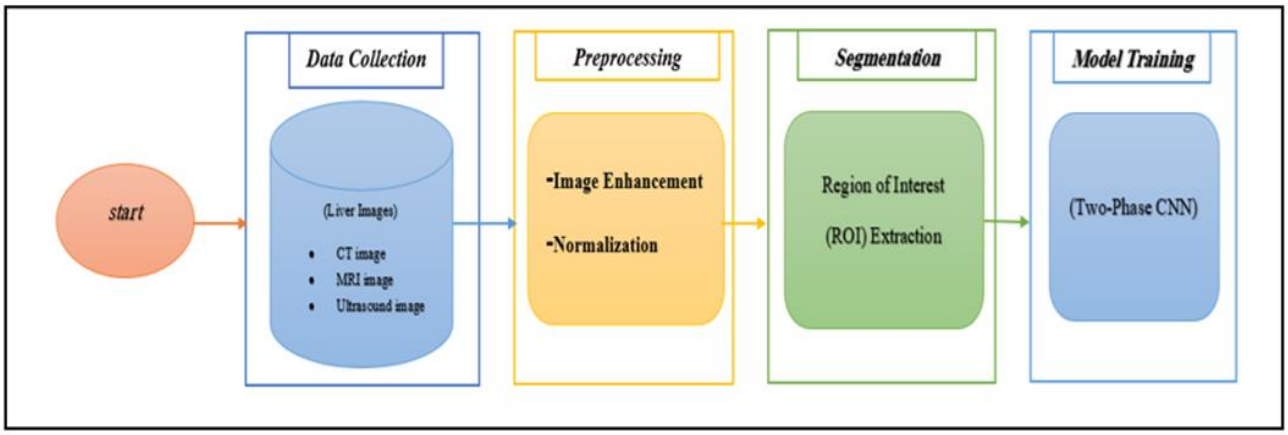

Figure 1: Block diagram of the methodology

2. Related works

In this section we will review previous studies. Taher et al. (2021) [1] focused on liver tumor classification using 352 ultrasound images (200 malignant, 152 benign) from a hospital. They employed traditional tumor segmentation and region-of-interest (ROI) selection determined by diagnosticians. A convolutional neural network (CNN) trained on the tumor regions achieved 90% accuracy with AlexNet and 92% accuracy with ResNet18. Priyadarsini et al. (2022) [2] conducted liver tumor classification on a CT image dataset from 48 patients (benign and malignant tumors). Preprocessing steps included grayscale conversion, normalization, noise removal, and segmentation to enhance growth region detection. Using the NRSVM classifier, the study achieved 96% accuracy, 90.56% sensitivity, and 98.63% specificity. Mubasher et al. (2022) [3] proposed a framework using 1,000 CT images from 100 patients. Their method included preprocessing, image enhancement, and feature extraction (55 features reduced to 20).

Random forests delivered the best results with 97.48% accuracy, 96.5% sensitivity, and 98% specificity. Random trees and logistic trees also showed strong performance.

Yoshihiro et al. (2022) [4] addressed liver cirrhosis classification with ultrasound images (200 healthy, 300 cirrhotic). Diagnosticians manually identified ROIs. Their CNN model achieved 30.6% accuracy, 85% sensitivity, and 90% specificity. Durga et al. (2022) [5] analyzed a CT dataset (130 images for training, 70 for testing). Segmentation through the K-means algorithm identified ROIs. The SVM classifier achieved 97% accuracy, 96% sensitivity, and 98% specificity. Jaya et al. (2023) [6] focused on classifying benign and malignant liver tumors using CT images. A region growth algorithm extracted ROIs. A support vector classifier achieved 91% accuracy, 100% sensitivity, and 33.3% specificity. Nosheen et al. (2023) [7] diagnosed liver diseases using a dataset of 583 Indian patients and 10 extracted features. A BiLSTM classifier yielded 93% accuracy, 91% sensitivity, and 90.88% specificity. Solomon et al. (2023) [8] utilized CT images (12 healthy, 24 infected cases). Deconvolution removed background noise, and median filtering enhanced quality. The ANN classifier achieved 95.8% accuracy, 100% sensitivity, and 91.7% specificity. EL-Sayed et al. (2024) [9] used machine learning algorithms and BPSO on an Indian liver disease dataset. The Incremental Tree Classifier model reached 79.82% accuracy and 48.28% sensitivity, improving to 85% accuracy with BPSO. Mahtab et al. (2024) [10] classified fatty liver disease with 64 ultrasound images. Using Bayesian networks and wavelet transforms, the accuracy reached 100%. Without the transform, results ranged from 81% accuracy, 67-93% sensitivity, and 93% specificity.

Akiho et al. (2024) [11] classified fatty liver disease using 30 ultrasound cases divided into three grades. A CNN trained on manually defined ROIs achieved 63.3% accuracy using heat maps. Daisuke M. et al (2025) [13] presented a study in which they used a single-center cross-sectional design including 517 cases suffering from chronic liver disease (CLD). Data were collected from ultrasound images of patients during examination and liver stiffness testing between August 2019 and October 2022. Deep learning algorithms such as convolutional neural networks were used to classify liver fibrosis cases, and a pre-trained model ResNet50, was used. The study aimed to evaluate the effectiveness and objectivity of artificial intelligence in diagnosing the stages of liver fibrosis.

3. Evaluation measures for classifications

To assess classifications and how well they predict the labels of classes, a number of measures are employed. F-Measure, sensitivity, specificity, accuracy, and precision (detection) are some of these requirements [12].

1. Accuracy: The proportion of precise predictions to the total sample. A higher accuracy score indicates a more accurate model [12].

$$accurcy = \frac{true\ positives + true\ negatives}{total\ instances} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

2. Sensitivity (Recall): Shows the model's ability to forecast the future. A high sensitivity means the model can accurately identify true positives [12].

$$\text{sensitivity} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

3. Precision: The ratio of confirmed positive predictions to all anticipated positive predictions [12].

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

4. Specificity: Evaluates how well the model can forecast unfavorable outcomes.

$$\text{specificity} = \frac{\text{true negatives}}{\text{true negatives} + \text{false positives}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

5. F1-score: The F1 Measure balances precision and memory by taking the harmonic mean of the two [12].

$$F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Together with the previously mentioned criteria, the confusion matrix, which is shown in table 1.

Table 1: confusion matrix

	Predicted positive	**Predicted negative**
Actual positive	True positive (TP)	False negative (FN)
Actual negative	False positive (FP)	True negative (TN)

4. Proposed Methodology

This approach aims to enhance the accuracy of liver disease detection and classification using advanced deep learning techniques. It utilizes two datasets: one comprising CT images categorized into cirrhosis, hepatitis, liver cancer, fatty liver, and normal, and another comprising ultrasound images classified as benign tumors, malignant tumors, and normal. Image segmentation plays a pivotal role in isolating regions of interest (ROI) and identifying liver centers to enable precise feature extraction. To ensure dataset uniformity, preprocessing techniques such as noise removal, normalization, and color adjustment are implemented. The methodology employs a two-stage convolutional neural network (CNN) architecture. In the initial stage, the CNN is trained on images where the region of interest (ROI) and liver centers are identified, utilizing data augmentation to achieve dataset balance.

In the subsequent stage, the remaining portions of the images are processed. Features extracted from both stages are merged through a feature fusion approach to produce comprehensive outputs. to enhance feature extraction, the framework integrates pre-trained deep learning models such as ResNet50, ResNet101, VGG16, and Inception, maximizing the model's performance and accuracy. The model's effectiveness is evaluated through cross-validation and performance metrics such as accuracy, sensitivity, specificity, and F1-score. This comprehensive, multi-stage approach significantly enhances the model's ability to deliver early and accurate liver disease diagnoses. The figure 2 shows the proposed methodology.

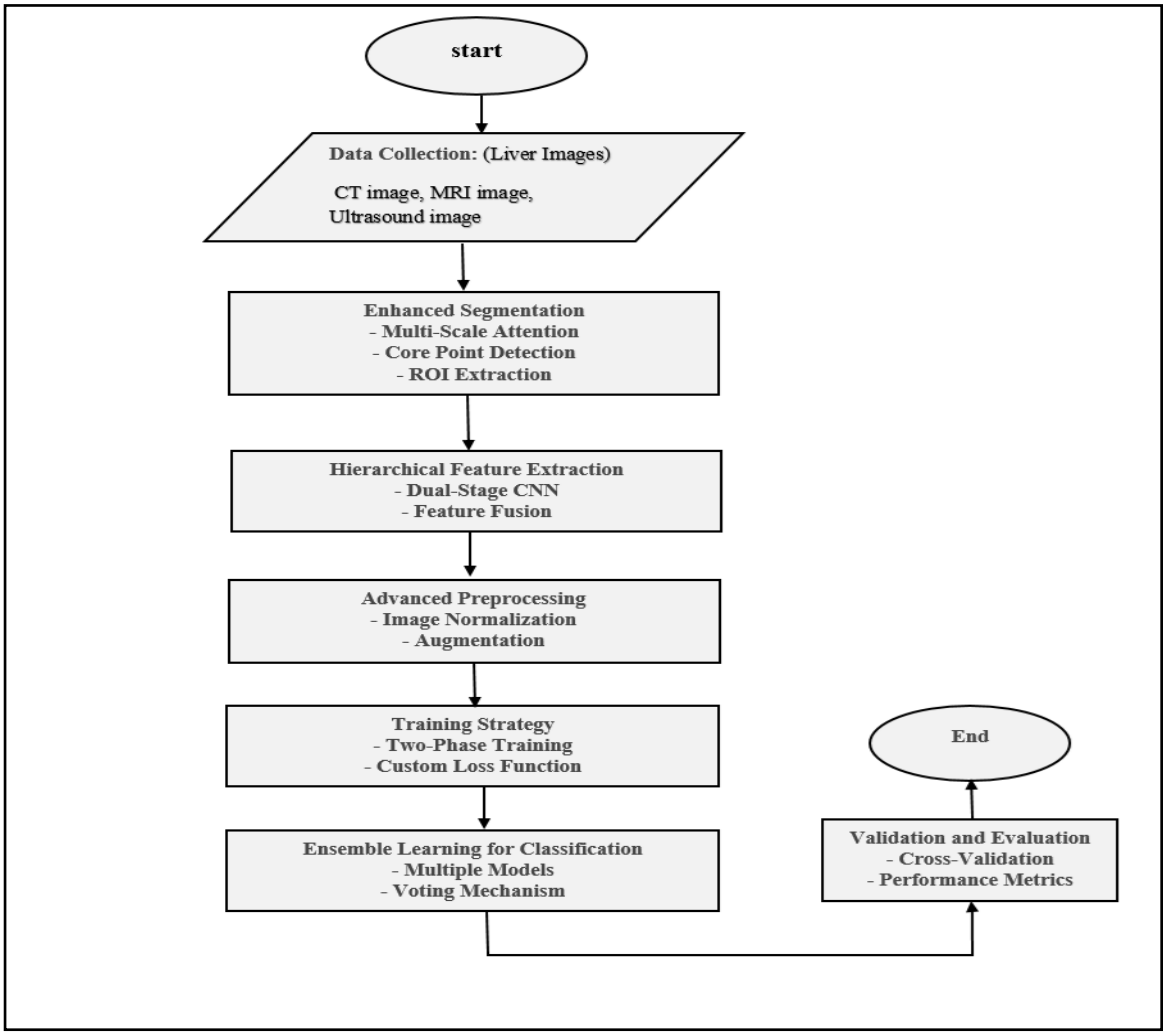

Figure 2: General structure of the model.

During the data collection phase, liver disease images were sourced from multiple datasets, including a diverse collection of CT scan images categorized into cirrhosis, hepatitis, liver cancer, fatty liver, and normal. Ultrasound images were also included, classified into three categories: benign tumors, malignant tumors, and normal.

In the second phase, image segmentation is conducted to precisely determine the liver's center. A multi-scale attention mechanism is utilized to allow the model to focus on the region of interest (ROI), facilitating the extraction of critical features and the accurate identification of the liver's center. Convolutional layers play a key role by enhancing the ROI, optimizing the extraction of essential features. The identified ROIs and their corresponding features are subsequently stored for use in the following stages. Figure 3 shows the CT images and how the Region of interest (ROI) was defined in our study.

Algorithm1: Image Segmentation

Input: Preprocessed images
Output: Images with identified ROIs and liver centers

1. Initialize segmentation parameters
   - Set threshold values for segmentation
   - Define method for identifying liver center
2. For each image in preprocessed_images do:
   3. Identify the Liver's Center:
      a. Analyze image to locate liver region
      b. Calculate center point (x_center, y_center)
      c. Store (x_center, y_center)
   4. Segment the Region of Interest (ROI):
      a. Define ROI based on center point and radius
      b. Extract ROI from original image
      c. Output segmented ROI image

5. Store segmented images in specified directory
End

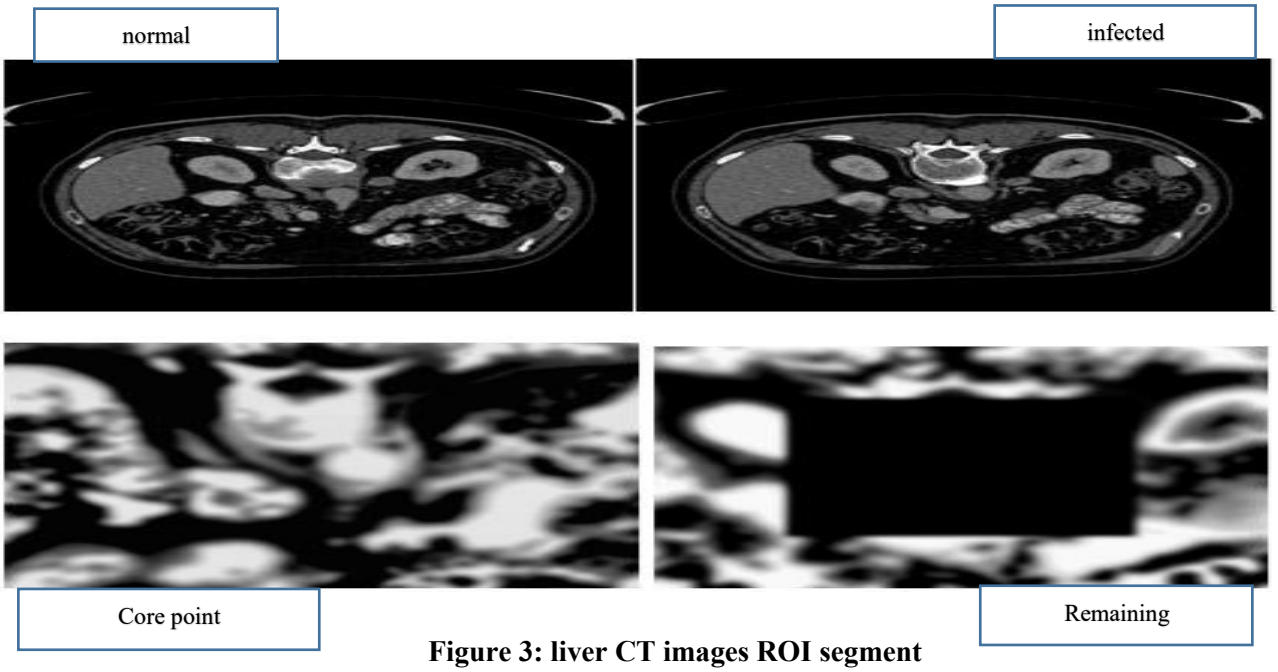

Figure 3: liver CT images ROI segment

In the third step of the proposed model, we will use deep learning algorithms such as advanced convolutional neural networks (CNNs), such as ResNet50, ResNet101, and VGG16. This step also builds a custom CNN consisting of two parts. The CNN is trained on the region of interest (ROI) taken from liver images, identifying its center point in the first part, and extracting features from this point. In the second part of this step, the CNN is trained, focusing on the remaining part of the image from which the center point was cut. The network is trained on this remaining part. Through this step, features are identified, a larger image is formed in the CNN, and learning is performed on liver images. Then, using feature fusion, we combine the training outputs of both parts, the center point and the remaining parts of the image, using the CNN algorithm 2 represents feature extraction.

Algorithm 2: Feature Extraction

Input: Trained CNN models from Stage 1 and Stage 2
Output: Combined feature set for classification

1. Initialize feature storage:
   - Create empty lists for features_ROI and features_remaining
2. For each image in segmented_images do:
   3. Extract features from ROI using Stage 1 model:
      a. Pass ROI image through Stage 1 CNN model
      b. Obtain feature vector for ROI
      c. Append feature vector to features_ROI
   4. Extract features from remaining image portions using Stage 2 model:
      a. Pass remaining image portion through Stage 2 CNN model
      b. Obtain feature vector for remaining portion
      c. Append feature vector to features_remaining
5. Combine features:
   - Create combined_feature_set by concatenating features_ROI and features_remaining

End

The fourth step involves image processing and advanced processing algorithms to improve model performance. Processing steps such as normalization, noise removal, contrast enhancement, and color enhancement are implemented step by step to ensure consistency and uniformity of images in the dataset. To increase classification accuracy, preprocessing and data balance are used. Data augmentation techniques, such as rotation, scaling, and reflection, can augment data in underrepresented datasets and increase model accuracy and generalizability by applying a diverse dataset. Figure 4, illustrates the advanced processing steps.

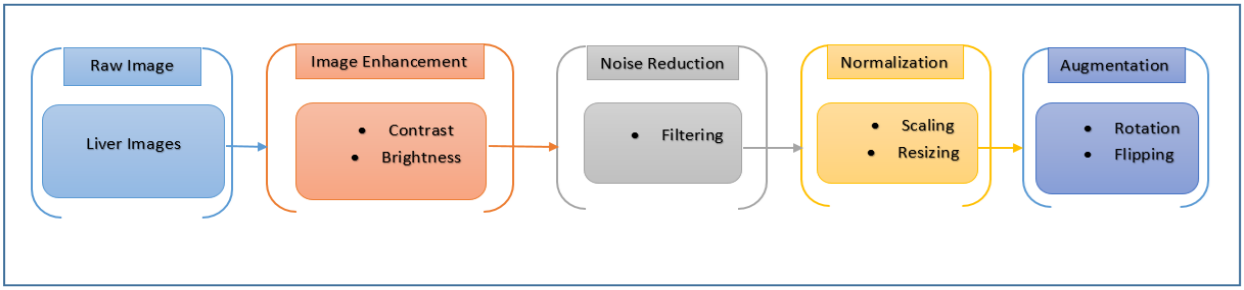

Figure 4: illustrates the advanced processing

In the fifth step, the data was divided into 70% training,15% testing, 15% validation. The model training occurs in two distinct stages. The initial stage focuses on training the convolutional neural network (CNN) with images in which the region of interest (ROI) is clearly delineated and the liver centroid is precisely identified. In the second stage, the convolutional neural network is trained on the remaining and central parts of the image, using the features collected from the central and residual liver images. The goal of this stage is for the model to integrate features and information more broadly and predict liver disease. We then add and calculate the data loss function, which helps ensure accurate classification in both stages, the liver centroid and the residual image and avoids class imbalance. Figure 5 illustrates the steps of the model training process, and algorithm3 representing and training CNN structure.

Algorithm 3: CNN Architecture Setup

Input: Segmented images with identified ROIs
Output: Trained CNN models for ROI and remaining images

1. Initialize CNN Architecture:
   - Define model architecture (two-stage CNN)
   - Set hyperparameters (learning rate, batch size, epochs)
2. For Stage 1 do:
   3. Prepare training dataset:
      a. Use ROI images for training
      b. Split dataset into training and validation sets
   4. Build CNN Model for ROI:
      a. Add convolutional layers
      b. Add activation functions (ReLU)
      c. Add pooling layers
      d. Add fully connected layers
      e. Compile model with loss function and optimizer
   5. Train CNN Model on ROI images:
      a. Fit model using training dataset
      b. Validate model using validation dataset
6. For Stage 2 do:
   7. Prepare training dataset:
      a. Use remaining image portions for training
      b. Split dataset into training and validation sets
   8. Build CNN Model for remaining images:
      a. Follow similar architecture as Stage 1
      b. Compile model with loss function and optimizer
   9. Train CNN Model on remaining images:
      a. Fit model using training dataset
      b. Validate model using validation dataset

End

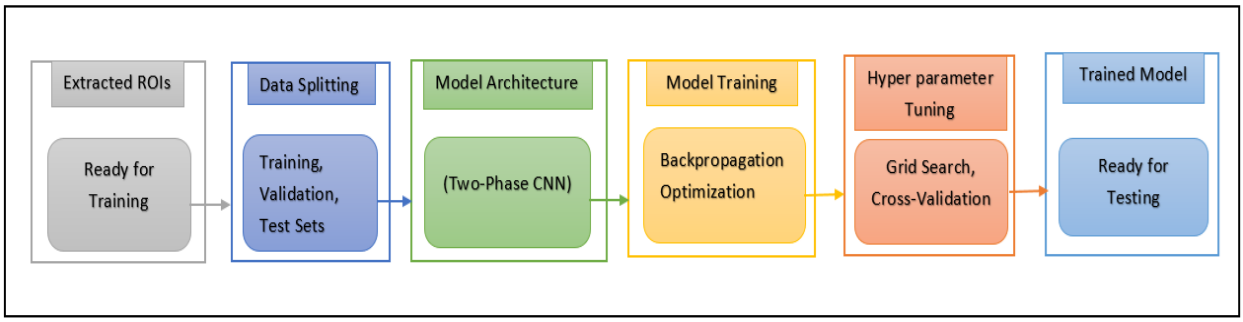

Figure 5: illustrates the model training

In the sixth step of the study, which includes the use of multiple classification models which are already trained and which can pick up features and distinctive patterns of images and also can use the features that have been extracted from the nerve network. The purpose of using multiple multi-coach works and models is the correct and accurate prediction of classification, and deep learning algorithms that are already trained like ResNet50, ResNet101, VGG16, and Inception.

In the seventh step of the proposed methodology, we will evaluate the performance of the model and verify its effectiveness. We used cross-validation and applied it to the model. The goal of this is to ensure the performance of the model and its generalizability in general. We used basic metrics and calculated the confusion matrix, where the accuracy, sensitivity, and specificity (F1-score) were calculated, and the model was tested on new and diverse data. Figure 6 illustrates evaluate the model.

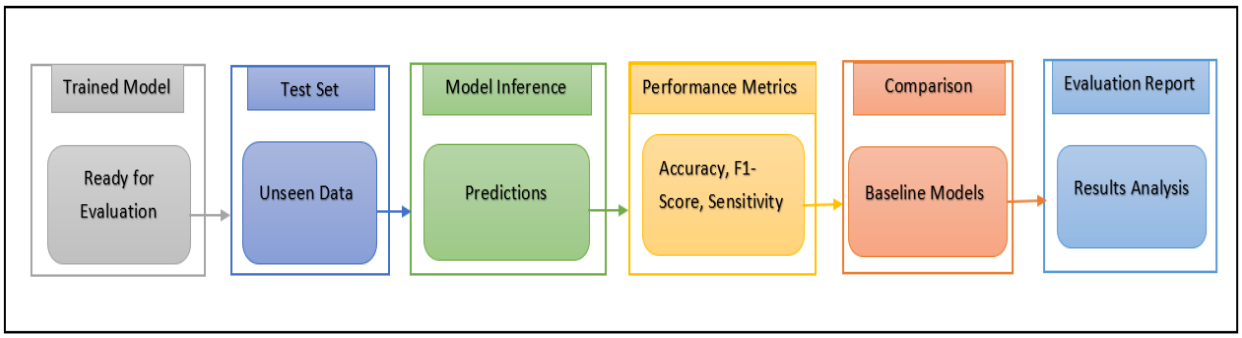

Figure 6: illustrates evaluating the model

5. Results and discussions

In this section, we will discuss and analyze the results and the environment in which the proposed methodology was implemented, compare the results with previous studies, and evaluate the performance of the model.

5.1 Dataset description

In this section, we will describe the dataset used, which was collected from a Kaggle dataset and consists of two diverse datasets. The first dataset consists of CT scan images, which were classified into two categories: diseased and non-diseased. The diseased category consists of four categories: cirrhosis, hepatitis, liver cancer, and fatty liver. The non-diseased category contains images of a healthy liver. The second dataset consists of ultrasound images, which are divided into two categories: diseased and non-diseased. The diseased category contains two types of tumors, benign and malignant, while the non-diseased category contains images of a healthy liver. The dataset was split into training and test and validation sets at a ratio of 70:30%.

5.2 Model performance

In this section, we will evaluate the performance of our proposed model, which was implemented on an MSI laptop with 8 GB RAM, Windows 11 (64-bit), and a Core i7 processor. Using MATLAB R2023a, we achieved good results compared to previous studies. Table 1 the classification accuracy of our proposed model and figure7 shows the proposed model results.

Table 2: The classification accuracy of our proposed model.

Propose model	Accuracy	Precision	Recall	F1_score
Resnet50	97.94%	97.77%	98.05%	97.86%
Resnet101	97.42%	97.80%	98.03%	97.85%
Vgg16	92.97%	93.45%	92.07%	92.66%
CNN	92.11%	94.02%	93.36%	93.57%

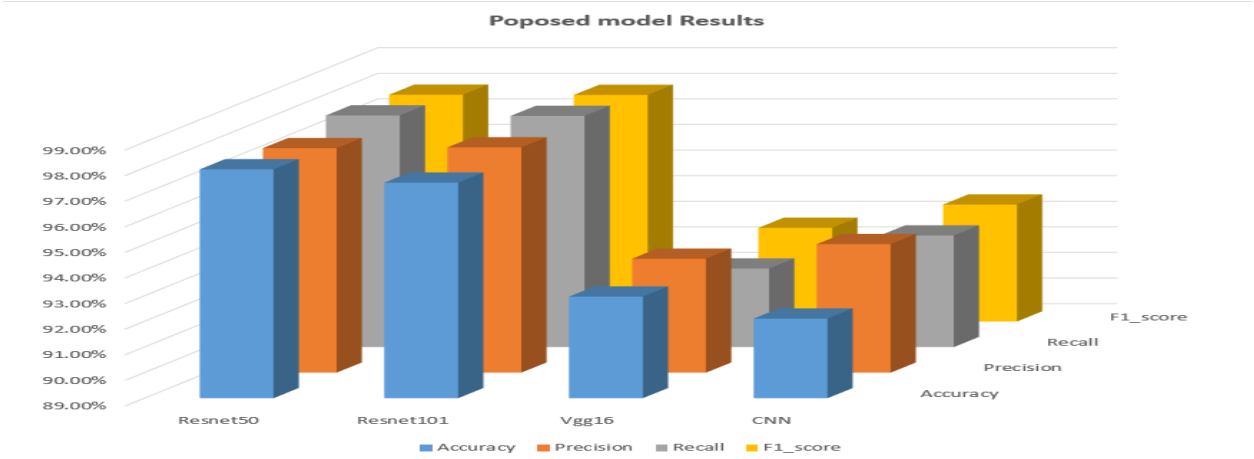

Figure 7: shows the proposed model results.

Figure 8 below shows the results of the confusion matrix from which basic metrics such as sensitivity and specificity, and F1-Score were calculated.

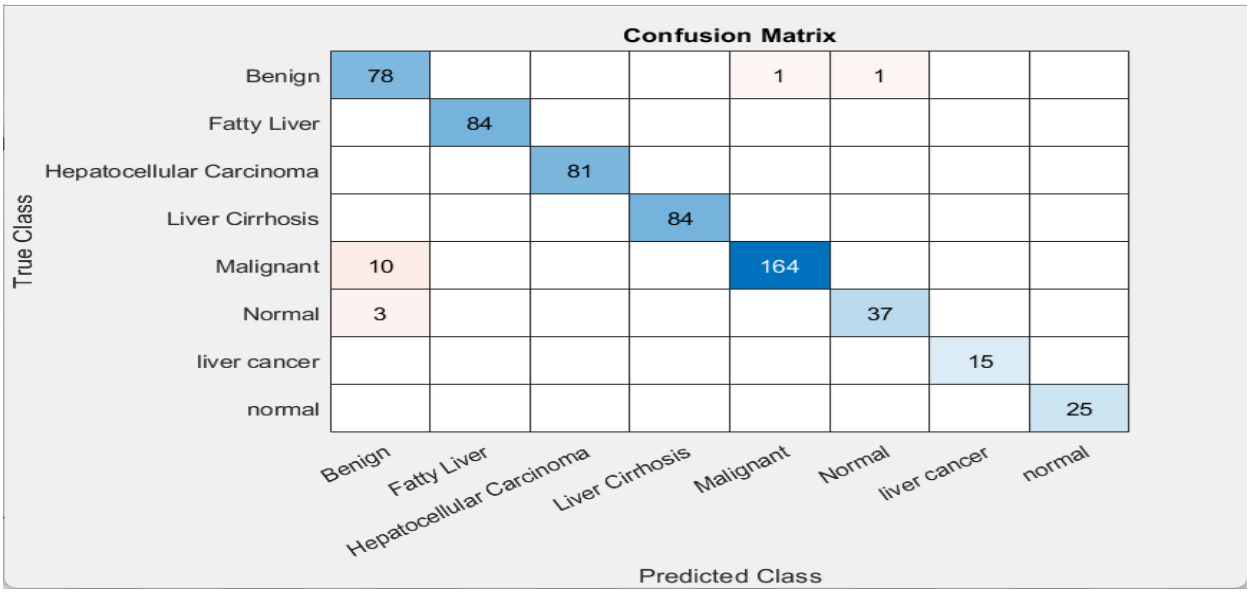

Figure 8: shows a confusion matrix for classification

5.3 Comparison with Previous Studies

In this section, we will compare the results of our proposed model with previous studies. Based on the results shown in Table 1 and compared with previous studies, our proposed model demonstrates a significant improvement in classifying liver diseases using deep learning algorithms. The Resnet50 model achieved a success rate of 97.94%, while the Resnet101 model achieved a success rate of 97.42%, and the CNN model achieved a success rate of 92.1%. These performance metrics significantly outperform many models used in clinical studies. For example, a study using CNN with Alexnet reported an accuracy rate of 92% [1]. [2] used the NRSVM model and achieved an accuracy of 96%, [3] used random forests and achieved a classification accuracy of 97.48%, [4] used machine learning classifiers and achieved an

accuracy of 97% using SVM. Although some studies, including those conducted by [5], have provided promising results, the results of our proposed model, which used advanced neural networks such as Resnet50 and Resnet101, have significantly outperformed and led to significant improvements in the accuracy of liver disease classification. Furthermore, previous studies show significant variation in results. For example, [5] reported that a CNN model was used and achieved an accuracy of 30.6%, highlighting the complexities and obstacles in this field. In conclusion, the findings of our proposed model underscore the remarkable potential of deep learning techniques in advancing the accuracy of liver disease diagnosis. This progress holds significant promise for enhancing healthcare delivery and improving patient outcomes. Table3 a comparison of the results with previous studies, and figure 9, shows the comparison using the basic evaluation metrics.

Table 3: Comparing results with previous studies.

Article	Approach	Accuracy	Precision	Recall	F1_score	Specificity
[1]	CNN with Alex Net	90%	-	-	-	-
	CNN with Resnet18	92%				
[2]	NRSVM	96%	90.56%	-	-	98.63%
[3]	RF	97.48%	96.5%	-	-	98%
[4]	ANN	95.8%	100%	-	-	91.7%
[5]	CNN	30.6%	85%	-	-	90%
[6]	SVM	97%	96%	-	-	98%
[7]	SVM	91%	100%	-	-	33.3%
[8]	Bi-LSTM	93%	91%	-	-	98%
[9]	ML	79.82%	48.28%	-	-	
[10]	NB	81%	93%	-	-	93%
[11]	CNN	63%	-	-	-	-
Proposed model	CNN	92.11%	94.02%	93.36%	93.57%	
	Resnet101	97.42%	97.80%	98.03%	97.85%	
	VGG16	92.97%	93.45%	92.07%	92.66%	
	Resnet50	97.94%	97.77%	98.05%	97.86%	

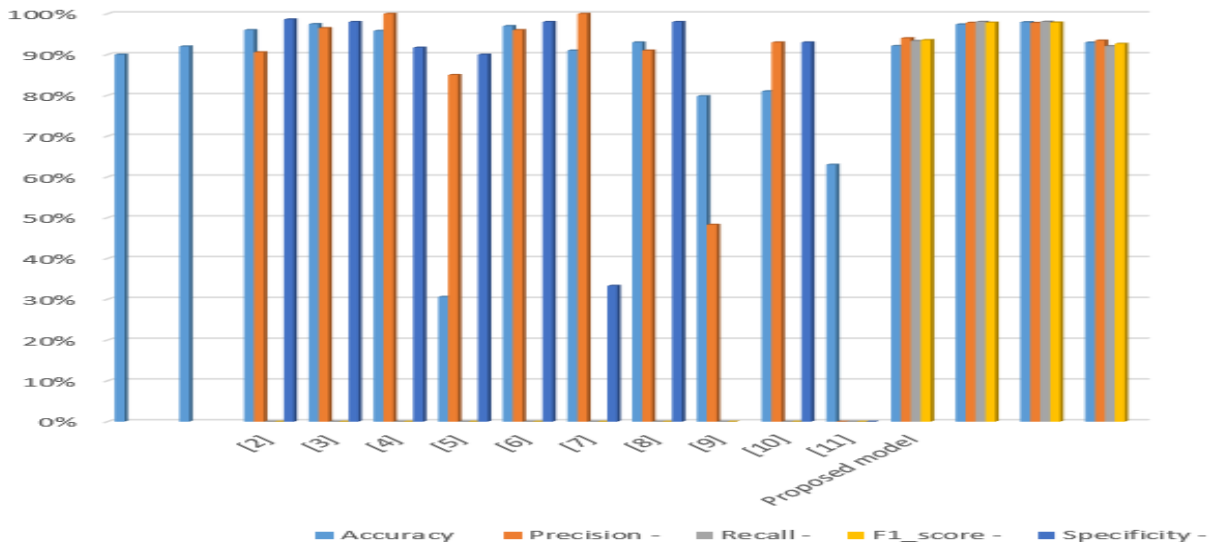

Figure 9: Comparison using the evaluation metrics.

6. Conclusion and Future Work

In summary, deep learning algorithms, particularly ResNet50 and ResNet101, have proven to be highly effective in detecting and classifying liver diseases. Their exceptional diagnostic accuracy has greatly enhanced clinical diagnostic capabilities, paving the way for more precise and reliable medical diagnoses. Therefore, they have been adopted for disease classification due to their high capabilities, and the results confirm their effective role in addressing healthcare challenges. Future research should aim to achieve the following suggested points:

- These models can be further developed and improved through hyperparameter tuning.
- Using a more diverse dataset and different imaging techniques can improve the model's generalizability and reliability, increasing diagnostic reliability.
- Liver diseases can be accurately identified and classified, such as fatty liver, as there are multiple types of fatty liver.
- Improving the interpretability and predictability of model predictions is crucial to gaining physicians' confidence and making informed decisions when diagnosing patients. By discovering these pathways, medical diagnosis can be enhanced, and the treatment of liver diseases can be made more effective.

Conflicts of interest

There is no conflict of interest in this research.

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