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Advancements and Challenges in Liver Image Analysis methods based on artificial intelligence for liver disease diagnosis

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The integration of artificial intelligence (AI) and deep learning models in the medical field has fundamentally transformed the attitude of healthcare practitioners toward disease diagnosis and management. A highly promising field is the identification and categorization of liver computed tomography (CT) images. These technologies allow for unparalleled precision in detecting the state of the liver, whether it is healthy or exhibits irregularities. Given its metabolism and detoxification function, the liver organ is of utmost importance in the body. Rapid and precise diagnosis of liver disorders is crucial for the well-being of patients. Surgeons employ conventional techniques for diagnosing liver conditions. These procedures heavily depend on the proficiency of radiologists, which might occasionally result in diagnostic inaccuracies. To address this constraint, researchers in the field of medical analysis have demonstrated that models tailored for image analysis and utilizing deep learning, especially convolutional neural networks (CNNs), have facilitated notable progress in this domain. These models have the capability to assess many CT scan images of liver organs and acquire the ability to recognize the unique characteristics of both healthy and sick livers. This methodology enables the early identification of liver problems, facilitates more efficacious interventions, and enhances clinical outcomes. This research highlights the importance of using AI and deep learning models to detect and categorize liver CT images. It will emphasize the benefits of these models in terms of precision, efficiency, and dependability in diagnosing liver ailments. Another promising avenue in liver disease recognition involves the utilization of elasticity properties. In this context, non-invasive techniques such as ultrasound elastography, transient elastography, and magnetic resonance elastography provide valuable insights into liver steatosis, fibrosis, and inflammation. We will explore the ethical implications and obstacles linked to this technical progress and its possible influence on the fields of medicine and healthcare.

Keywords: artificial intelligence; Image Analysis; disease diagnosis.

1. Introduction

Artificial intelligence has made substantial progress in the early detection of diseases, using AI algorithms to recognize different medical disorders based on patient data and medical images. These technological breakthroughs offer the potential for earlier detection of medical conditions and enhanced results for patients. AI-powered telemedicine and remote monitoring systems, particularly crucial amid the COVID-19 pandemic, provide remote consultations and ongoing monitoring of vital signs. The development of artificial intelligence (AI) applications helps in the quick and accurate identification of anomalies in X-rays, MRIs, and CT scans, which benefits the field of radiology. AI enhances personalized medicine using genetic data, clinical histories, and patient-specific information to customize treatment approaches. AI-guided robotic surgery improves accuracy and reduces mistakes in minimally invasive treatments. AI-powered mental health chatbots and applications provide assistance and track emotional well-being, aiming to enhance the availability of mental healthcare. Moreover, AI-powered chatbots and virtual assistants are becoming more advanced, enabling seamless patient interactions, efficient appointment booking, and effective dissemination of health information. The growing use of AI in healthcare has shifted focus towards resolving ethical issues and guaranteeing transparency and interpretability in deep learning algorithms, specifically in crucial medical decision-making processes. These algorithms improve the accuracy of predictive analytics, helping healthcare providers anticipate patient requirements and allocate resources efficiently, particularly in hospital administration and emergency triage. Deep learning offers a range of model architectures for classifying medical images, including liver CT imaging. Convolutional Neural Networks (CNNs) are frequently employed due to their versatility in handling various jobs, allowing for the adjustment of depth and width according to the intricacy of each specific scenario. Several deep learning architectures, such as ResNet, are employed to classify CT images due to their notable depth. They have the ability to acquire highly intricate characteristics. ResNet-50, which is a lighter variant, is frequently employed for the purpose of classifying medical images. The VGG (Visual Geometry Group Networks) topologies are renowned for their straightforwardness and effectiveness. They frequently serve as initial reference points for the classification of medical images. Additionally, recent developments in medical imaging have made it possible to investigate elasticity properties as a non-invasive way to evaluate liver diseases. The adoption of elasticity-based approaches in hepatological research signifies an interesting change in the identification of liver disease. This research provides a comprehensive analysis of artificial intelligence-based methodologies in addition to recent non-invasive techniques for diagnosing liver diseases. Various methodologies have been proposed to categorize and identify liver disease, employing diverse criteria. This research paper presents a comprehensive overview of the existing literature in the field

2. Exploring Image Analysis tasks in Liver Medical Imaging

The analysis and interpretation of medical images require four primary tasks: classification, localization, detection, and segmentation. Categorizing image analysis applications into one of these four areas is difficult due to the fact that they are usually performed in a mixed manner, regardless of this differentiation. Classification is the process of ascertaining the specific category or designation to which an object in an image belongs. The main categorization difficulties in liver image analysis are around discerning the liver from other organs, discriminating between damaged and healthy liver tissue, and ascertaining the nature of lesions as either benign or malignant. Image categorization is often integrated with localization, which involves determining the exact coordinates of the desired item inside the image. Categorizing image analysis applications into one of these four areas is difficult due to the fact that they are usually performed in a mixed manner, regardless of this distinction. Classification is the process of identifying the specific category or designation of an object or image. The main obstacles in liver image analysis revolve on the tasks of accurately identifying the liver in relation to other organs, discerning between damaged and healthy liver tissue, and categorizing lesions as either benign or malignant. Localization, the process of determining the exact coordinates of a certain item inside an image, is often used in conjunction with image classification. The object localization job generates a bounding box that contains the exact position of the primary object in the image. Localization is sometimes employed as a first step in more complex tasks, such as segmentation in medical image analysis. In order to reduce the computational complexity and processing time of these future tasks, it is possible to narrow down the search area by determining the region with the highest likelihood of possessing the required anatomical structure.

The segmentation algorithm achieves this objective by allocating each pixel to its corresponding class, namely, the appropriate category of tissue or organ. The segmentation may be categorized into two distinct types: instance segmentation and semantic segmentation (Fig 1). On the one hand, instance segmentation assigns a distinct label to each separate item inside a certain class. On the other hand, semantic segmentation assigns the same name to all pixels or objects belonging to the same class, for example, labeling all lesions as simply "lesion". Accurate segmentation assists radiologists in effectively treating the affected area while minimizing damage to healthy tissue during liver resection surgery and radiation therapy.

3. Artificial neural networks

Artificial Neural Networks (ANN) are designed to imitate the neural system of humans. Artificial neurons, which are the constituent processing units of ANNs, bear resemblance to the neurons found in the human brain [1]. Similar to actual

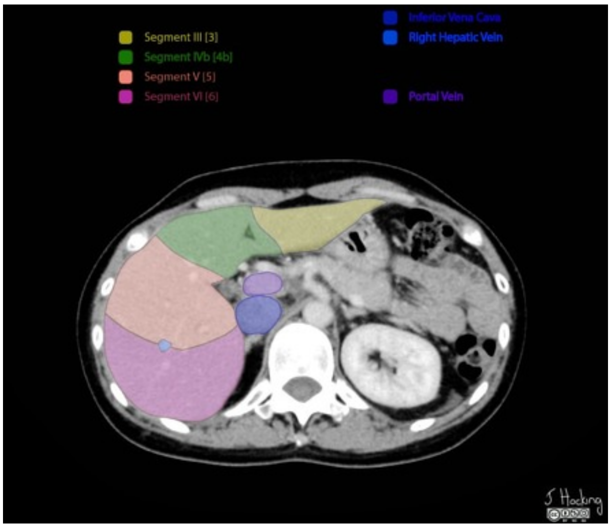

Fig. 1. Liver segmentation using annotated CT scans.

neurons, these units are interconnected through axons, which facilitate the passage of information between the neurons. Conversely, artificial neural networks (ANNs) represent this information as a numerical value produced by the activation function of the neuron, but in the nervous system, it is encoded as electrochemical impulses. The activation function is applied to the aggregate of the inputs received by the neuron, which are weighted and summed for processing. The learnable qualities of a neuron encompass the weights and the bias factor. Artificial neural networks (ANNs) consist of neurons arranged in stacked layers. A Multi-Layered Perceptron (MLP) is created by stacking numerous layers on top of each other. The generic network architecture has an input layer, many hidden layers, and an output layer. The input layer of a system receives the training observations or inputs. The synaptic weights of the neurons are adjusted to acquire and encode the correlations and patterns present in the data. This is achieved by the employment of hidden layers. The output layer is responsible for organizing the output according to the specified goal, such as utilizing numerical numbers for regression tasks or probabilities for classification tasks. The output layer gets the results from the hidden layers. Artificial neural network (ANN) learning systems may be classified into three main categories: supervised, unsupervised, and reinforcement learning. Supervised learning employs a task-oriented methodology. Commonly, its primary uses revolve around categorizing and predicting data by analyzing past knowledge. Supervised learning involves training the network by using input data and its matching accurate output, which is referred to as the ground truth. The characteristics of the artificial neural network (ANN), such as its weights and biases, are modified repeatedly by comparing the predicted value with the observed value. The training techniques in this category include backpropagation, commonly referred to as backward propagation. Semi-supervised learning, an innovative approach to supervised training, has experienced a substantial surge in its utilization. This technique is equally data-driven, but, it does not have access to the ground truth, unlike supervised training. However, the expected result is pre-established and used to evaluate the production [2]. When constructing descriptive models for a dataset, unsupervised learning is a data-centric approach that assigns equal significance to all attributes and does not imply a pre-established purpose. The primary use of artificial neural networks (ANNs) is in solving clustering problems. Reinforcement learning differs from the latter approach by utilizing interactions with the environment to acquire information.

3.1. *Deep learning approach*

A Convolutional Neural Network (CNN) is a computational model that employs convolutional layers to identify and classify certain local features present in the input images [3,4]. Convolutional layers use a series of filters made up of neurons to produce distinct activation or feature maps from the input. Every individual neuron receives a specific portion of the input image as its input, with the possibility of overlap, until the entire image is sampled. In contrast to multi-layer perceptrons (MLPs), each filter neuron or perceptron in this scenario possesses shared input weights with its adjacent neurons. As a result, the neurons demonstrate consistent sensitivity to identical local characteristics across all input channels. Kernels, often referred to as convolutional kernels, are specific collections of common weights. A convolutional layer including N convolutional kernels produces N feature maps, which are responsible for acquiring and identifying N local features. After each series of convolutional layers, it is standard practice to incorporate a pooling layer. This layer takes information from neighboring areas, regardless of whether they overlap or not, and combines it to decrease the size of the feature maps. Max-pooling layers enhance translation invariance by selecting characteristics with the most significant response. A convolutional neural network (CNN) employs a series of convolutional and pooling layers, together with fully connected layers (MLP), and a softmax or regression layer (the output layer) to generate its outcomes. This methodology involves integrating the Multilayer Perceptron (MLP) into the classification process while utilizing a combination of convolutional and pooling layers for feature extraction, which is more efficient than the traditional methodologies.

3.2. *Machine encoders*

An autoencoder (AE) is an unsupervised artificial neural network (ANN) that can efficiently train, compress and encode data. It can then restore the compressed data to a representation that nearly matches the original input [5]. An autoencoder (AE) comprises three primary components: the encoder, bottleneck, and decoder. During the learning process, the encoder develops techniques to encode data more efficiently by compressing and decreasing the input. The buried layer houses the compressed representation, which is the most succinct rendition of the input data. This reduced representation acts as the limiting factor. The decoder use its algorithmic prowess to optimize the decoded output, aiming to closely replicate the original data. The reconstruction loss assesses the level of similarity between the rebuilt data and the original data during the training phase. The backpropagation technique is used during training to reduce the loss in reconstruction. An ideal autoencoder model would have an appropriate level of sensitivity to properly produce a reconstruction, while avoiding excessive sensitivity that might result in memorizing or overfitting the training data. This tradeoff allows the model to ignore irrelevant information and only store the necessary data changes needed to reproduce the input data. Autoencoders, also known as AEs, provide a more extensive kind of principal component analysis (PCA) as they possess the capability to effectively reduce dimensionality. Both principal component analysis (PCA) and autoencoders (AEs) are effective in capturing non-linear manifolds. They both aim to select a lower-dimensional hyperplane that best reflects the input data. A deep autoencoder is a particular sort of autoencoder that employs numerous layers for both the encoding and decoding processes.

3.3. *Generative Adversarial Network*

A generating Adversarial Network (GAN) comprises a generating neural network and a discriminator neural network [6]. The generator network replicates the characteristics of the source dataset to produce original data. There is a clear and direct relationship between the output of the generator and the input of the discriminator. The main purpose of the discriminator network is to determine the source of the data it receives, differentiating between the training set and the data produced by the generator network. Through the backpropagation process, the generator updates its weights to include the classification signal that the discriminator provides. Throughout the training phase of Generative Adversarial Networks (GANs), the generator and discriminator partake in a competitive interplay. The generator network strives to reduce the disparity between the created and authentic data, while the discriminator network, conversely, endeavors to increase this distinction.

4. Liver disease recognition using AI methods

Several methods investigate the Artificial intelligence method to recognize liver disease from non-healthy liver organs. In order to analyze the different type of liver lesions, researchers explore the application of deep learning methods, specifically convolutional neural networks and fully convolutional networks, in medical image analysis. In [7] Authors examines the analysis of liver lesions, such as hepatocellular carcinoma and metastatic cancer, as well as liver structures like the parenchyma and vascular system. In this work, the authors highlight the use of deep learning in several imaging techniques, such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound. The authors focuses on the application of deep learning in tasks including segmenting, detecting objects, and classifying liver-related structures such as the liver organ, hepatic vessels, and liver lesions. The presented results have shown that hybrid models yielded improved results for liver and lesion segmentation. Additionally, these classifiers proved to be more successful for vascular segmentation. A mixed strategy was found to be superior for lesion classification and detection. The evaluation measures employed were the Dice coefficient for segmentation and accuracy for classification and detection. The results emphasize the significance of integrating pertinent data into deep learning models, including shape and edge contours, local and global context, and the use of multi-scale and multi-plane inputs, along with pre- and post-processing techniques to enhance performance. However, they focus on the importance of further enhancement, specifically in tackling the difficulties associated with the diversity of medical images and liver structures. Researchers investigate the augmentation strategies to generate varied and annotated medical data to train deep learning models. This work emphasizes that liver vessel segmentation and classification are underexplored domains in DL-based medical image analysis. Although current research mostly focuses on segmenting the liver from CT scans, which is an increase for analyzing liver images using several imaging techniques, particularly for minimally invasive surgical procedures. The authors also propose that transfer learning networks could effectively tackle the difficulties related to extending deep learning approaches to various modalities. Since the segmentation of the liver is important for computer-aided decision support systems and medical diagnosis, Mubashir et al. [8], propose a highly effective technique for segmenting the liver in computed tomography (CT) images, using deep learning. In order to tackle the difficulties presented by indistinct borders, the authors use a stacked autoencoder (SAE) to acquire discernible liver characteristics from abdominal CT images. In contrast to conventional pixel-by-pixel methods, their methodology employs image patches for feature learning. They preprocess the dataset by enhancing the images and transforming them into overlapping patches. The patches are fed into the SAE (Stacked Autoencoder) for unsupervised feature learning. Then, the model is fine-tuned and used for classification to generate a probability map in a supervised way (Fig. 2). The experimental results substantiate the efficacy of the suggested approach, attaining a 96.47% Dice Similarity Coefficient (DSC), surpassing other existing methodologies.

The model is efficient and reliable, performing liver segmentation on a per-slice basis with a tolerable duration of 9 seconds per slice. By training on patches, the occurrence of misclassification is reduced and the need for human feature engineering is eliminated, hence simplifying the procedure. In this paper, the authors showcase the comparison between their outcomes and other methodologies, illustrating the better efficacy of their method. The authors aim to investigate more discerning deep learning architectures for liver segmentation using larger datasets.

Fig. 2. Segmentation results generated by Mubashir et al. [8] model.

Liver tumors can be categorized as either benign or malignant, with malignant tumors carrying a greater potential for adverse health effects. In the field of classifying and detecting liver cancers, V. Durga et al. [9] introduce a novel approach by employing image processing and machine learning methodologies. The primary objective of this work is to investigate the implementation of fuzzy histogram equalization as a preprocessing technique for noise reduction in images. The images are further partitioned into pieces to precisely identify areas of interest. Three classification methodologies are used: the RBF-SVM technique, the ANN technique, and the random forest technique. The authors assessed the efficacy of these algorithms by analyzing a dataset obtained from multiple clinical sites across the globe. The test dataset consisted of 70 CT scans, whereas the training dataset contained 1030 CT scans. The classifiers were evaluated according to their accuracy, sensitivity, and specificity. The results obtained suggest that the SVM RBF algorithm has unparalleled accuracy and specificity in the categorization of liver cancers. Moreover, artificial neural networks (ANNs) exhibit a higher level of sensitivity compared to the currently available approaches. In order to predict liver disease and support the surgeon to make decisions regarding the diagnosis of liver patients, Md. Fazle et al. [10] conduct a comparative analysis that focuses on predicting liver problems through the use of machine learning algorithms. Their work underscores the significance of early detection in reducing the likelihood of severe liver conditions, such as liver cancer. The Indian Liver Patient Dataset (ILPD) is used to test 4 machine learning algorithms: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and Extra Trees (ET). The authors use the Pearson correlation coefficient-based feature selection (PCC-FS) method to remove unnecessary features from the dataset. Then, they implement the AdaBoost boosting algorithm to improve the predictive performance of these techniques. The evaluation measures used for comparison encompass accuracy, ROC, F-1 score, precision, and recall. According to the input data, the ET algorithm achieves a maximum accuracy of 92.19%. The results are carried out in Google Colab, utilizing 10-fold cross-validation to accurately evaluate the efficacy of the machine learning algorithms. The dataset is divided into an 80:20 ratio, with 80% used for training and 20% used for testing. Before implementing feature selection, the LR, DT, RF, and ET models attain accuracies of 68.75%, 84.86%, 86.9%, and 90.76%, respectively. The AdaBoost method moderately improves the performance of these algorithms. To tackle the problem of imbalanced class distribution, a Random over-sampler is employed during the data preparation step. In addition, Robust Scaling is used to modify the dispersion of feature values. Nevertheless, the outcomes are considered inadequate, which leads to the use of PCC-FS to enhance the algorithms. Among them, ET achieves the highest accuracy of 92.19%. Also, Aviral et al. [11] provide a comprehensive analysis of different machine learning (ML) algorithms used to predict patient liver disease. In this paper, authors use 3 machine learning techniques: Naive Bayes, K-Nearest Neighbor (KNN), and Logistic Regression to investigate the application of machine learning (ML) algorithms to predict liver illness automatically. The authors highlight the significance of information systems and strategic tools in medical research to improve disease detection. However, the early diagnosis of liver illnesses might be difficult due to the lack of distinct symptoms, resulting in potential neglect. The authors propose the use of different machine learning techniques, namely Logistic Regression (LR), Naive Bayes Model (NB), and K-Nearest Neighbor (Knn), to accurately diagnose and validate the existence of liver illness by analyzing enzyme levels. Within this proposed framework, data is classified into two distinct categories: individuals afflicted with liver disease and those who are not afflicted. Various machine learning algorithms are used, and their performance is evaluated using diverse criteria to determine the most precise approach for forecasting the occurrence of liver disease. The correctness of these distinct algorithms is evaluated by employing diverse performance indicators. Out of the assessed algorithms, the Logistic Regression model achieved the best accuracy of 75% in comparison to the other models. To emphasize the prediction, analysis, and storage of medical data and the computer-assisted diagnosis in the medical images. Muthuselvan et al. [12] examine the categorization of individuals with liver conditions by employing machine learning algorithms. The liver patient dataset is employed for training and evaluating machine learning algorithms, using the WEKA program for implementing diverse classification techniques. Upon executing all the algorithms, the paper determines the most effective algorithm by evaluating their outputs. In this paper, authors employ a confusion matrix to classify the data into two categories: patients with a disease and patients without a condition. The process consolidates all the data into a unified dataset and uses the WEKA classification algorithms to execute the classification, employing the confusion matrix. The main objective of this project is to use machine learning algorithms to evaluate data gathered from the North East region of Andhra Pradesh in India. The algorithms are implemented to categorize individuals as either having liver disease or not having it. The Random Tree algorithm achieves maximum accuracy with a nominal execution time. This proposed method proves the efficacy of employing machine learning algorithms in forecasting liver illness, providing useful insights for the medical domain. However, this is limited due to the longer execution duration compared to other algorithms. The liver's vital roles, including nutrient digestion, toxin filtration, and immune defense, are emphasized as primary factors contributing to its importance in maintaining good health. Different machine learning (ML) models and ensemble approaches are assessed and contrasted based on performance metrics such as Accuracy, Precision, Recall, F-Measure, and the area under the curve (AUC), to predict the presence of liver disease. Elias et al. [13] investigate the application of machine learning in predicting liver illness. In this paper, authors identifies the Voting classifier as the most precise approach among the ones examined, suggesting its potential utility in clinical practice and healthcare research. To overcome this limitation, authors investigate the use of machine learning (ML) algorithms to forecast liver illness. The presented results in this work indicate that the Voting classifier surpasses other models, attaining an accuracy rate of 80.1%, a precision rate of 80.4%, a recall rate and F-measure of 80.1%, and an AUC of 88.4% following the implementation of the Synthetic Minority Over-sampling Technique (SMOTE) with 10-fold cross-validation. Authors presents prior research that use the Indian Liver Patients' Records dataset and the developed models. It emphasizes that the voting approach employed in this study outperforms such models in terms of accuracy. The objective of this research is to assist physicians and researchers in the monitoring of liver disease, the creation of customized high-performance models, and the integration of quality-of-life aspects that accurately represent the well-being of patients. Nevertheless, it recognizes the constraints associated with the dataset and proposes additional investigation to enhance the accuracy of liver disease prediction systems by integrating deep learning methodologies. Since the importance of early detection of Liver Disease, Ghazal et al. [14] propose an intelligent model that exhibits remarkable accuracy and minimal misclassification rates. This model has the potential to facilitate early diagnosis and enhance patient care. In this paper, authors highlight the capacity of machine learning (ML) to automate the diagnosis of liver illness and present an advanced approach that uses machine learning techniques to accurately forecast liver disease. The proposed model is specifically engineered to improve the precision of early detection. The suggested model exhibits good performance, achieving an accuracy of 88.4% and a miss-rate of 0.116. During the validation step, the developed model undergoes testing using a total of 19,660 samples. These samples are categorized into positive cases, representing liver disease, and negative cases, representing no liver illness. The model accurately predicts the presence or absence of liver disease in a significant proportion of the samples, with only a few misclassifications. The proposed model employs an efficient Artificial Neural Network (ANN) technique to reliably and promptly forecast liver illness, which is vital for minimizing complications and ensuring appropriate treatment. Machine Learning is an algorithmic approach employed to identify patterns in extensive datasets, facilitating decision-making. Several ML classification methods are investigated for predicting liver disease in patients, such as Logistic regression, Decision Tree, Random Forest, K-Nearest Neighbor, Gradient Boosting, Extreme Gradient Boosting, and LightGB. In this context, Gupta et al. [15] conducted a study that used machine learning classification approaches to forecast liver illness in patients. The results of their study indicate that the LightGB algorithm outperformed the other algorithms in terms of accuracy. The Liver Patient dataset used in this work is sourced from the UCI Repository and belongs to the domain of supervised learning. The collection comprises data about individuals who underwent medical evaluations at healthcare, with a specific emphasis on patients with liver conditions. For analyzing and categorizing the data, the authors use historical patient data to forecast future patient outcomes. In addition, the authors provide a detailed description of the data pretreatment stages, including strategies for managing missing values and encoding categorical variables, as well as techniques for removing outliers in order to improve the performance of the model. The presented results prove that the Random Forest, LightGB, and AdaBoosting algorithms outperform other classification methods in terms of accuracy. In addition, authors indicate that the LightGB algorithm is well employed for the prediction of liver illness. This study examine the application of deep learning-based auto-segmentation in contrast to atlas-based auto-segmentation for organ structures in patients with liver cancer. In this study, the authors assess the potential of deep learning-based auto-segmentation in addressing these limitations and compare its performance with standard approaches. In this context, the authors use contrast computer tomography (CT) imaging sets from 70 patients with liver cancer. They manually outlined four organs at risk (OARs) - the heart, liver, kidney, and stomach - as reference structures. The authors employed both atlas-based approaches and a deep convolutional neural network (DCNN) to carry out auto-segmentation. The segmentation algorithms were evaluated using several metrics, such as Hausdorff distance (HD), dice similarity coefficient (DSC), volume overlap error (VOE), and relative volume difference (RVD). The presented results demonstrate that the deep-learning-based approach surpassed the atlas-based approach for the majority of organs at risk (OARs). Although there are certain limitations, such as inconsistencies in the segmentation outcomes caused by factors like the existence of gas bubbles and differences in stomach shapes, the deep learning-based approach generally produces more precise results for the organs at risk (OARs). Furthermore, the authors propose that the use of deep learning-based auto-segmentation can effectively be employed for the majority of organs at risk (OARs) in patients with liver cancer, thereby diminishing the duration needed for contouring in radiation therapy planning. The results affirm the practicality of using deep learning algorithms for auto-segmentation, especially in the context of daily adaptive plans that incorporate multiple imaging techniques. In the field of analyzing magnetic resonance imaging (MRIs) of the liver and pancreas, Alan et al. [16] present the use of deep learning methods to forecast abdominal age. In this study, the authors aim to comprehend the process of aging in abdominal organs such as the liver and pancreas. The proposed method constructs an "AbdAge" predictor using convolutional neural networks (CNNs) that were trained on a substantial dataset of liver and pancreatic MRIs. The predictor had a high level of accuracy in predicting abdominal age, as seen by an R-Squared value of 73.3 ± 0.6. Additionally, the authors exhibited a mean absolute error of 2.94 ± 0.03 years. Subsequently, attention maps were generated by the CNNs, which indicated that the prediction of abdominal age is influenced by anatomical characteristics of the liver and pancreas, as well as adjacent abdominal structures and tissues. The authors of this study calculated the degree to which accelerated abdominal aging is influenced by genetics and discovered specific genetic locations that are linked to this characteristic. Significant contributions of genetic variables to accelerated abdominal aging have been identified, with specific genetic connections with age-related disorders such as macular degeneration. Notably, genes such as PLEKHA1 and EFEMP1 have been implicated in this process. Furthermore, an X-Wide Association Study (XWAS) was carried out to identify biomarkers, clinical phenotypes, illnesses, environmental factors, and socioeconomic variables linked to accelerated abdominal aging. Correlations were identified in other areas, including body impedance, blood pressure, and pulse wave analysis, indicating probable factors that may increase the risk and clinical measures associated with abdominal aging. This study offers valuable insights into the process of aging in abdominal organs and its possible implications for age-related disorders. The authors have enhanced their understanding of the processes that contribute to abdominal aging and its connections with different health-related variables through the use of deep learning and genetic analysis.

5. Liver disease recognition using elasticity properties

Elasticity properties play a crucial role in the recognition and diagnosis of liver diseases, particularly when considering technologies like elastography, which measures tissue stiffness or elasticity. Liver diseases can cause changes in the composition and structure of liver tissue, leading to alterations in its mechanical properties of the liver organ. In this context, Camelia et al. [17] aimed to evaluate the severity of liver fibrosis and liver steatosis in patients with Alcohol Use Disorder (AUD) using non-invasive tests and propose a screening algorithm for Alcoholic Liver Disease (ALD). The study included 172 subjects with positive AUDIT-C scores, and the results showed that 13.9% had advanced fibrosis and 17.% were newly diagnosed with liver cirrhosis. Significant correlations were found between liver stiffness and non-invasive biological scores, with the Fibrosis-4 index (FIB-4) and age-platelet index being independently associated with advanced fibrosis. The performance of non-invasive fibrosis scores and AUDIT-C for predicting advanced fibrosis was evaluated, and FIB-4 was found to have good accuracy in the diagnosis of advanced liver fibrosis. The study also discussed the implications of liver steatosis and the use of non-invasive tests for screening ALD. Overall, the findings provide a basis for noninvasive screening in patients with AUD and suspected ALD, with a proposed algorithm for easy recognition and specific follow-up in primary care. The study's limitations included the lack of a liver biopsy and precise information on alcohol consumption. However, the results emphasize the importance of non-invasive testing in identifying liver complications in patients with AUD. Numerous studies have been conducted on Non-alcoholic fatty liver disease (NAFLD), the most prevalent chronic liver disease worldwide. NAFLD affects around 38% of the general population and up to 80% of individuals with diabetes. In [18] researchers aim to compare the accuracy of liver ultrasound elastography and FIB-4 with liver biopsy in ruling out cirrhosis in obese non-alcoholic Fatty Liver Disease patients at a tertiary transplant referral center in the USA. This study involved 93 patients who underwent liver ultrasound elastography, liver biopsy, and FIB-4 calculation. The results showed that a cut-off value of 12.5 kilopascals (kPa) for F4 had a 92% sensitivity and 54% specificity in ruling out cirrhosis, with values below this threshold excluding cirrhosis with 98% certainty. Ultrasound elastography demonstrated higher accuracy in ruling out cirrhosis compared to FIB-4, with 92% sensitivity and 98% negative predictive value. The study also highlighted the significance of NAFLD as the most common cause of advanced liver disease in the USA, with potential progression to cirrhosis and hepatocellular carcinoma. Liver biopsy, the gold standard for evaluating liver fibrosis, is associated with risks and limitations, leading to the exploration of noninvasive diagnostic tests such as ultrasound elastography and FIB-4. Ultrasound elastography was found to be superior to FIB-4 in ruling out cirrhosis in obese NAFLD patients at a 12.5 kPa cut-off, thereby helping to avoid the risks and expenses associated with liver biopsy. The accuracy of ultrasound elastography and FIB-4 in ruling out cirrhosis was compared based on liver stiffness measurement and pathology results obtained from liver biopsy. The findings suggested that ultrasound elastography with a 12.5 kPa cut-off was highly accurate in ruling out cirrhosis in obese NAFLD patients and showed better accuracy than FIB-4 values. However, the study acknowledged several limitations, including the retrospective nature of the data analysis and the small sample size. In [19] authors have evaluated the non-invasive methods for assessing liver fibrosis in NAFLD patients. NAFLD is characterized by the abnormal accumulation of fat in hepatocytes and encompasses a spectrum from simple and benign deposition of fat to more aggressive non-alcoholic steatohepatitis (NASH) leading to fibrosis, cirrhosis, and hepatocellular carcinoma. The prevalence of significant fibrosis, advanced fibrosis, and cirrhosis in NAFLD patients is reported as 45.0%, 24.0%, and 9.4%, respectively, with similar rates as in viral hepatitis patients. The non-invasive transient elastography and 2D-shear wave elastography have demonstrated good accuracy in diagnosing significant fibrosis in NAFLD patients, with 2D-SWE showing a sensitivity and specificity of 90% and 93%, respectively, for the identification of advanced liver fibrosis. However, the diagnostic accuracy of strain elastography alone is limited, and future studies are needed to explore its potential in combination with other ultrasound-based elastography methods. In order to diagnose the Chronic HCV infection, Rihab et al. [20] evaluate the effectiveness of ultrasound elastography as a non-invasive method for diagnosing and staging hepatic fibrosis in individuals with chronic liver diseases caused by HCV. Chronic HCV infection is a significant cause of liver illnesses globally, particularly in Egypt. The study compares ultrasound elastography to liver biopsy, the current gold standard for assessing liver fibrosis, and finds that ultrasound elastography is highly sensitive and specific, particularly for detecting advanced fibrosis and cirrhosis. Real-time tissue elastography (RTE) proves to be particularly useful for identifying early cirrhosis and advanced hepatitis. The limitations of liver biopsy, such as invasiveness, discomfort for the patient, variability, and sampling errors, are discussed. The correlation between the liver fibrosis index and liver fibrosis stage, as identified by liver biopsy, shows a strong positive connection with high sensitivity and specificity, especially in identifying high grades of fibrosis. The study also compares the performance of ultrasound elastography techniques with transient elastography, demonstrating their efficacy in quantifying liver stiffness. The effectiveness of ultrasound elastography is further supported by the correlation between various parameters such as the liver fibrosis index, histological fibrosis stages, and activity. The findings show strong positive connections between these parameters, enhancing the method's diagnostic performance. The research work discusses the significance of ultrasound elastography in predicting advanced fibrosis, cirrhosis, and severe fibrosis. The potential benefits of real-time tissue elastography and transient elastography in accurate fibrosis diagnosis are also highlighted. The authors suggest that further research on larger patient cohorts will be necessary to validate ultrasound elastography and determine its potential to replace liver biopsy. In [21] authors aimed to summarize and compare studies on elastographic liver stiffness in patients with Wilson's disease. Their work highlights the wide range of symptoms of liver dysfunction in Wilson's disease patients, with liver involvement often manifesting as asymptomatic elevation of liver enzymes or acute liver failure. The paper discussed various elastography techniques, including transient elastography and shared wave elastography, as reliable and repetitive alternatives to liver biopsy. However, the limitations and challenges of these techniques were also highlighted, leading to the introduction of magnetic resonance elastography (MRE) as a potential non-invasive method for liver fibrosis evaluation. While MRE shows promise, its limitations in terms of availability, cost, and practicality for long-term surveillance in Wilson's disease patients were identified. The paper detailed several studies that evaluated elastography alone or in combination with serological markers for liver fibrosis assessment in Wilson's disease patients. It discussed the variability in elastographic liver stiffness values in different stages of the disease, and how repeated measurements may be useful for assessing disease progression or regression. However, the research indicated that a single measurement of liver stiffness may not be sufficient for accurately staging fibrosis in Wilson's disease, and a combination of non-invasive assessment methods increases the chance of a more precise evaluation. The authors concluded that significant progress has been made in utilizing elastography for liver fibrosis assessment in Wilson's disease, but more research is needed to establish expert consensus on specific liver stiffness cutoff values for different stages of fibrosis. In order to assess the correlation between liver stiffness measurement (LSM) and serum fibrosis markers to detect advanced liver fibrosis, authors in [22] explore the prevalence and importance of chronic liver disease (CLD) and liver fibrosis, focusing on the Czech Republic. Chronic liver disease affects about 1.5 billion people globally, with the most common causes being non-alcoholic fatty liver disease (NAFLD), hepatitis B virus (HBV), hepatitis C virus (HCV), and alcoholic liver disease (ALD). A total of 89 patients with various liver diseases participated in the study and underwent ultrasound examination, vibration-controlled transient elastography (VCTE), as well as serum tests such as AST to Platelet Ratio Index (APRI), Fibrosis-4 (FIB-4) score, and enhanced liver fibrosis (ELF) test. The results showed that about 20.2% of the patients had advanced fibrosis as assessed by LSM. The study found significant correlations between LSM values and serum fibrosis markers, and highlighted the effectiveness of APRI and FIB-4 as simple tools for screening liver disease in primary care, irrespective of the etiology of liver disease. The findings also indicated that individuals younger than 38.1 years had a low risk of advanced liver fibrosis. The study underlines the need for noninvasive diagnostic methods due to the limitations of liver biopsy, emphasizing the importance of early assessment of liver fibrosis for patient management. The research signifies the significance of identifying patients with advanced fibrosis to ensure they receive the necessary medical attention and treatment. It also highlights the dynamic nature of the fibrogenesis process, pointing to the importance of noninvasive methods in monitoring disease progression and adjusting management strategies accordingly. The paper also highlights the limitations of the study, such as the relatively small sample size, and points towards future research directions for validating the findings further. Ludivine et al. [23] investigate the use of transient elastography (TE) as a method to screen for compensated advanced chronic liver disease (cACLD) in patients with alcohol-related liver disease who are undergoing alcohol withdrawal. This study included 259 patients who were hospitalized for alcohol detoxification. Liver stiffness measurement by TE was found to be an accurate method for identifying patients with or without advanced fibrosis/cirrhosis, with high accuracy values at both inclusion and at the 1- and 2-month follow-up evaluations. The study found that TE is effective at ruling out cACLD when liver stiffness is less than 10 kPa and ruling in cACLD when greater than 25 kPa. Additionally, the study observed that among patients with initial liver stiffness values of 10 to 25 kPa, more than half of those with no cACLD showed liver stiffness of less than 10 at the follow-up testing. The research suggests that TE performed during the first 2 months after alcohol cessation is an excellent method for excluding alcohol-related cACLD. The study also reported that liver stiffness varied with time and was associated with alcohol withdrawal, with the decrease in liver stiffness being mainly driven by patients without cACLD. Furthermore, the diagnostic performance of TE remained high at the 1- and 2-month follow-up evaluations. The study concludes that two months from the beginning of care is a suitable period to assess fibrosis by TE in heavy drinkers identified from primary care, hepatology clinics, or addiction units and recommends repeating TE if patients are in the grey area and resume drinking. The findings emphasize the potential of TE to improve cACLD diagnosis performance and provide insights into the optimal intervals for further evaluation in patients with ongoing or recent alcohol withdrawal. In [24], researchers discuss ultrasound-based methods for evaluating patients with NAFLD, which has become a major focus of hepatology in the developed world, overtaking chronic viral hepatitis. NAFLD affects over a quarter of the global population, with factors like obesity, diabetes, and metabolic syndrome contributing to its prevalence. The proposed terminology of Metabolic Associated Fatty Liver Disease (MAFLD) aims to better reflect the disease's clinical spectrum. The evaluation of fibrosis severity is crucial, and various non-invasive biologic tests, such as FIB-4 or APRI, are available for predicting significant fibrosis in NAFLD patients. Additionally, ultrasound-based elastography techniques, including transient elastography and shear wave elastography, have shown practical value in assessing liver fibrosis. The study concludes that ultrasound methods are crucial for assessing NAFLD patients, and that screening individuals at risk for fatty liver using modern ultrasound tools is a challenge for the near future. The ongoing development of these ultrasound techniques holds promise for the non-invasive assessment of NAFLD patients. Chunli Li et al. [25], discuss the challenges of chronic liver disease (CLD), its major causes, and the limitations of current clinical standards for assessment. It highlights the invasive nature of liver biopsy and its limited capability for screening and monitoring. The paper emphasizes the potential of noninvasive methods, specifically three-dimensional magnetic resonance elastography (3D MRE), for comprehensive assessment of CLD. 3D MRE is described as a simple, fast, safe, and noninvasive technology that can provide comprehensive insight into increased liver stiffness beyond stage-specific fibrosis. The technology exhibits considerable potential for assessing early necroinflammation, discriminating necroinflammation from fibrosis, detecting nonalcoholic steatohepatitis severity, predicting cirrhosis complications, and identifying tumor recurrence. The paper concludes by urging for the clinical application and promotion of 3D MRE technology in China to improve treatment selection in CLD patients and facilitate its widespread use. The study also includes a summary of various research studies based on 3D MRE for detecting liver inflammation, assessing liver fibrosis, predicting cirrhosis complications, and identifying tumor recurrence. The paper provides comprehensive insight into the potential benefits and applications of 3D MRE as a noninvasive technology for assessing and managing chronic liver disease. In [26] authors assessed the agreement between the Ishak scoring system and magnetic resonance elastography-measured liver stiffness (MRE-LS) in children with chronic liver disease. A total of 52 patients were included in the study, with MRE-LS values found to be significantly different between different Ishak fibrosis stages. MRE-LS had high sensitivity and specificity for differentiating mild/moderate fibrosis from severe fibrosis. It was moderately correlated with the Ishak fibrosis score and histological activity index, and weakly correlated with a spartate amino transferase and hepatic steatosis. However, only Ishak fibrosis score was a significant predictor of MRE-LS. MRE-measured spleen stiffness was weakly correlated with the Ishak fibrosis score. The study concluded that MRE has high sensitivity and specificity for evaluating liver fibrosis in children, and may potentially replace biopsy for this purpose in the future. The paper highlighted the potential limitations of liver biopsy and the benefits of non-invasive methods like MRE for assessing liver fibrosis in children. The study emphasized the importance of further research to establish normal liver stiffness values in healthy children and to evaluate MRE in different etiologies of chronic liver disease. The findings indicated the potential for MRE to serve as a non-invasive tool for liver fibrosis assessment in pediatric patients, with high sensitivity and specificity for detecting different stages of fibrosis.

6. Discussion

Focusing on liver-related segmentation tasks, this paper provides a complete comparative overview of recent works in the field of medical image analysis. The discussed studies collectively underscore the transformative impact of artificial intelligence (AI) and machine learning (ML) in the realm of liver disease recognition and prediction. Leveraging advanced techniques such as deep learning, these investigations focus on tasks like liver and lesion segmentation, vascular segmentation, and the classification of diverse liver-related structures. Hybrid models emerge as a promising strategy, demonstrating superior outcomes in lesion classification and detection. Challenges related to diverse medical images and liver structures are acknowledged, urging the prioritization of augmented datasets and further research. This study also highlights the underexplored domain of liver vessel segmentation and emphasizes the growing demand for applying deep learning to varied imaging modalities. Machine learning algorithms play a pivotal role in predicting liver cancer, with specific models, such as SVM RBF and LightGB, showcasing remarkable accuracy. Furthermore, the integration of deep learning and genetic analysis offers insights into the aging processes of abdominal organs, presenting potential implications for age-related disorders. In essence, these studies collectively contribute to the ongoing evolution of AI and ML applications in enhancing the diagnosis, segmentation, and prediction of liver diseases. A comparative study of the highlighted liver disease recognition methods using AI techniques (section 4) is presented in Table 1.

Table 1 : Comparative studies in medical image analysis for liver disease recognition.

	Methodology	AI Technique	Results	Limits
Shanmugapriya et al. [7]	Deep learning in liver image analysis	CNN, FCN,	Hybrid models for accurate segmentation	Specific focus on liver image analysis, not a broad overview
Mubashir et al. [8]	Liver segmentation using deep learning on CT images	Stacked Autoencoder (SAE)	Achieved high DSC (96.47%)	Limited to liver segmentation from CT images
V. Durga et al. [9]	Classification and detection of liver tumors using ML	SVM, ANN, Random Forest	SVM RBF algorithm for liver tumor classification	Limited to classification and detection tasks
Md. Fazle et al. [10]	Liver disorder prediction using ML algorithms	Logistic Regression, Decision Tree, Random Forest, Extra Trees	Achieved high accuracy (92.19%)	Limited to liver disorder prediction, not broader liver aspects
Aviral et al. [11]	Review of ML algorithms for liver disease prediction	Naive Bayes, K-Nearest Neighbor, Logistic Regression	-Logistic Regression achieved high accuracy (75%)	Limited to review, no direct implementation or results
Muthuselvan et al. [12]	Classification of liver patients using ML algorithms	Random Tree	Random Tree achieved high accuracy with nominal time	Limited to classification of liver patients, not comprehensive
Elias et al. [13]	ML prediction of liver disease with Voting classifier	Various ML models and ensemble methods	- Voting classifier outperformed with 80.1% accuracy	- Limited discussion on specific models or their limitations
Ghazal et al. [14]	Intelligent ML model for predicting liver disease	ML techniques with ANN	Achieved high accuracy (88.4%), low misclassification	Limited discussion on potential limitations or challenges
Gupta et al. [15]	ML classification techniques for liver disease prediction	Random Forest, LightGB, AdaBoosting	LightGB algorithm yielded best accuracy	Limited discussion on challenges or potential drawbacks
Alan et al. [16]	Predicting abdominal age using deep learning on liver and pancreas MRIs	Convolutional Neural Networks (CNNs)	Achieved high R-Squared value (73.3 ± 0.6)	Limited to predicting abdominal age, not a broader health context

Liver diseases pose a significant concern for global health, necessitating early and accurate diagnosis for effective management and intervention. In recent years, there has been a growing interest in the utilization of elasticity properties as a non-invasive approach to identify and assess liver conditions. Elasticity-based techniques, including ultrasound elastography, transient elastography, and magnetic resonance elastography, offer valuable insights into liver steatosis, fibrosis, and inflammation, obviating the need for invasive procedures like liver biopsy. The use of elasticity-based techniques has the potential to revolutionize the field of hepatology by furnishing safer and more accessible diagnostic instruments. The following comparative table 4 presents a comprehensive overview of various research studies focused on the recognition of liver diseases through the assessment of multiple properties. The studies employ various non-invasive methods such as ultrasound elastography, transient elastography, and magnetic resonance elastography to evaluate different liver diseases such as steatosis, fibrosis, and inflammation in different clinical contexts. The objectives, methods, advantages, and limitations of each study are outlined, highlighting the innovative approaches, diagnostic accuracy, and potential challenges associated with these elasticity-based techniques.

Table 2 : Comparative overview of Liver disease recognition method based on organ elasticity properties.

	Methodology	Parameters	Advantages	Limits
Camelia et al. [17]	-Assess the severity of liver steatosis and liver fibrosis in patients with alcohol use disorder (AUD)	-Vibration-controlled transient elastography (VCTE) with Controlled Attenuation Parameter (CAP).	-Cost-effective. -good accuracy in diagnosing advanced liver fibrosis. -Early recognition of severe alcoholic steatohepatitis	- VCTE is costly and limited to specialized liver centers. - No clinical parameters or diagnostic methods can accurately predict ALD.
Sofi et al. [18]	-Compare the accuracy of Ultrasound Elastography (UE) and FIB-4 in ruling out cirrhosis in NAFLD patients.	-Transient elastography (FibroScan) with an XL probe was used for LSM. -93 patients were involved. -CAP parameter, FIB-4 index and Liver stiffness measurement (LSM) were obtained.	-UE is safe, quick, and the cheapest radiographical test. -UE is Superior to FIB-4 values in both sensitivity and negative predictive value. -Highly accurate in ruling out cirrhosis.	-Liver biopsy is associated with significant risk and expense. -Limitations in sampling error and variability. -Small sample size for testing.
Rosanna et al. [19]	-Evaluate the non-invasive methods for assessing liver fibrosis in NAFLD patients.	-Ultrasound-based techniques (transient elastography, ARFI techniques, strain elastography). -Serum biomarkers.	-2D-shear wave elastography show good accuracy. -Serum biomarkers as new diagnostic options.	-Potential complications and sampling variability. -2D-shear wave elastography are not optimal for detecting low-grade fibrosis.
Rehab et al.[20]	-Determine the diagnostic performance of ultrasound elastography in predicting advanced fibrosis.	- Abdominal ultrasonography. -Ultrasound-guided liver biopsies. -Real-time elastography (RTE) to quantify the stiffness of the liver.	- Reproducibility. - No highly skilled operator required - Low risk of unfavorable results	-Limitations in sampling error and variability.

	Methodology	Parameters	Advantages	Limits
Piotr et al. [21]	-Determine the optimal procedure for assessing liver morphology in Wilson's disease.	- Transient elastography. - Shear wave elastography. - Magnetic resonance elastography (MRE).	- Liver stiffness decreases during copper-lowering therapy in Wilson's disease. -2D-shear wave elastography shows good accuracy.	- Standard imaging techniques have insufficient sensitivity to assess fibrosis accurately. -MRE has limitations in availability, cost, and duration.
Nikola et al. [22]	Assess the correlation between liver stiffness measurement (LSM) and serum fibrosis markers. Determine the usefulness of APRI and FIB-4 as screening tools for liver disease.	Vibration-controlled transient elastography (VCTE). AST to Platelet Ratio Index (APRI score). Fibrosis-4 (FIB-4) score. Enhanced liver fibrosis (ELF) test. Ultrasound examination.	Serum fibrosis markers can serve as a screening tool in primary care. APRI and FIB-4 are simple tools for screening liver disease.	VCTE is costly and limited to specialized liver centers.
Ludivine et al. [23]	Evaluate the performance of transient elastography (TE) for excluding alcohol-related cACLD. Assess the influence of alcohol consumption on liver stiffness (LS).	Prospective, multicenter study conducted in 6 hospitals in France.	TE has high accuracy in identifying patients with cACLD. TE is an excellent method for excluding alcohol-related cACLD.	Limitations in sampling error and variability.

7. Conclusion

Image processing methods based on artificial intelligence can enhance important structures and minimize background noise by integrating crucial factors such as

	Methodology	Parameters	Advantages	Limits
Ioan et al. [24]	Quantification of fibrosis, steatosis, and liver inflammation. Screening for fatty liver in patients with obesity, metabolic syndrome.	Standard ultrasound for steatosis detection. CAP for quantitative evaluation of liver steatosis. Liver stiffness assessment as a marker of fibrosis. Viscoelastic properties as a marker of inflammation	Ultrasound modules are widely implemented. Rapid evaluation of NAFLD (less than 5 minutes)	Some biologic tests for predicting fibrosis in NAFLD are complex and expensive.
Chunli et al. [25]	Evaluate the degree of liver injury in chronic liver disease (CLD). - Predict cirrhosis complications. - Identify tumor recurrence.	Elastography technique based on ultrasound and magnetic resonance imaging (MRI).	Simple, fast, safe, and noninvasive technology - Good diagnostic accuracy, reproducibility, and lower failure rate.	Expensive equipment with high technical requirements and complex operations. Limited research conducted with small sample sizes from single centers.
Duygu et al. [26]	The correlation between MRE-LS and Ishak fbrosis stage, MRE parameters, and clinical and biochemical markers.	Abdominal MRE and liver biopsy were performed on children. - MRE parameters and histological activity index were determined.	-MRE has high sensitivity and specifcity for evaluating liver fbrosis in children.	- Small number of patients without fibrosis and with severe fibrosis.

shape and edge contours, local and global contextual information, as well as pre- and post-processing techniques. Several deep-learning methods for liver lesion segmentation and classification are discussed in this paper to show how they might be able to help solve problems caused by the wide range of medical images and liver structures. To effectively apply the proven methods in clinical practice, researchers must also give priority to developing augmentation techniques that can artificially generate a diverse set of real-labeled medical data. This data can be used to train deep-learning models. The field of AI-based medical image analysis has not thoroughly investigated the research area of hepatic vascular segmentation and classification. The current AI-based methods primarily focus on segmenting the entire hepatic vasculature due to the complex structure of their design. Further studies should emphasize the challenge of distinguishing or classifying the hepatic and portal structures separately, as this has substantial clinical importance. Most of the present research focuses primarily on the segmentation of the liver using CT scans. In order to do computer-assisted liver resections, it is important to devise techniques capable of analyzing liver pictures obtained from several modalities. As interest in minimally invasive surgery increases, there may be an increase in research publications that aim to apply deep learning techniques to modalities like positron emission tomography (PET). Further exploration of the areas of adaptability and transfer learning networks can successfully address this challenge. In this paper, non-invasive elasticity-based methods for diagnosing liver conditions are described. These methods are used instead of invasive diagnostic procedures like a liver biopsy. Elasticity-based diagnostics show significant potential for revolutionizing the identification of liver diseases as the field progresses. Subsequent research endeavors should prioritize enhancing these techniques, tackling existing challenges, and exploring innovative ideas to enhance the practicality and precision of clinical applications and diagnostic efficacy. These studies serve as a foundation for ongoing discourse and exploration, providing valuable knowledge to the broader scholarly community.

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