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Liver Disease Diagnosis Using Machine Learning: A Review of Imaging-Based Methods

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ABSTRACT

Liver disease is one of the major health threats throughout the world. Among the different imaging modalities involved in diagnosing and managing liver conditions, Magnetic resonance imaging (MRI) and computerized tomography (CT) scan play a pivotal role. Various studies were focused on developing automated systems to detect and classify liver diseases using advanced image processing and machine learning algorithms. A review of the literature shows that machine learning models are capable of predicting liver disorders from MRI and CT images. Research indicates that deep learning techniques, especially convolutional neural networks (CNNs), surpass traditional approaches in the extraction and classification of features, thereby enhancing diagnostic accuracy and facilitating early disease detection. This study advances global healthcare initiatives by employing machine learning to enhance the precision of liver disease diagnosis and treatment, aligning with (Goal 3: Good Health and Well-Being). This also advances medical technology by fostering innovation in medical imaging and incorporating AI-driven solutions into healthcare systems (Goal 9: Industry, Innovation, and Infrastructure).

1. Introduction

Liver disease is still one of the most pressing challenges to public health around the world with a considerable burden of morbidity and mortality associated with conditions like cirrhosis, hepatitis, and hepatocellular carcinoma in a different stage[1][2] as shown in Fig1. Hence, an accurate and timely diagnosis is critical for appropriate treatment planning and favorable outcomes. The diagnosis of liver diseases usually depends on expert opinion based on medical images like CT scans and MRI scans. Liver lesion classification is a problem of application of great attention to computer-aided classification (CAD) by design and developmental systems that offer diagnostic support to clinicians with a higher degree of accuracy and reliability[3][4]. Such a CAD system for diagnosing liver cancer using full or at least substantial automation of the support of a radiologist includes three main operational stages: Liver division and lesion identification, feature extraction, and classification of liver diseases based on a classifier[5]. In recent years, non-supervised and less time-consuming automated tools have been under extensive investigation. Liver lesion segmentation is a challenging job to do because of low contrast between the liver, lesion, and the adjacent other organs[6].

Other additional difficulties are the uniformity in lesion size and noise in CT scans[7]. It's a hard problem to make a strongly combined system that can handle these problems. Recently, there have been found out some effective methods that are based on deep CNNs to cater for these problems[8]. Recent embracement of artificial intelligence, specifically image analysis through machine learning, promises the provision of more accurate and consistent diagnosis and assessment of liver diseases[9]. Usually, the quality of medical images is poor because of technical limitations. This inadequacy causes problems in the analysis of images leading to the wrongful decision in most cases. The quality of these images with medical image fusion also gets improved for better clinical applicability[10].

Comprising large datasets of medical images, these machine learning models happen to 'see' complex patterns and minute abnormalities that are beyond human detection. This all may be instrumental in optimizing diagnoses, minimizing diagnostic errors, and boosting physician decision-making competency[11].

However, use of machine learning in liver disease diagnosis has several challenges. First and foremost is the requirement for large, high-quality, well-annotated data sets to train models accurately[12]. Medical data acquisition faces problems such as privacy issues and the specialized expertise required for proper annotation. It is further realized that the difference in imaging protocols between different hospitals can affect how generalizable the models become, calling for modalities on how to standardize data inputs. secondly, while they may assist in diagnosis, they cannot replace clinical expertise; interpretability is a big concern, where clinicians have to understand and be confident in the decision-making processes of these models.

The development of liver disease diagnostic machine learning models from medical images is one of the most crucial steps towards United Nations (UN) Sustainable Development Targets, particularly Goal 3: Optimal health and wellness. This ensures early precise diagnosis followed by timely treatment and increased recovery rates, better patient quality of life, and extremely reduced healthcare costs [13]. They carry diagnostic services closer to the people, which will enhance universal health coverage in alignment with Goal 10: Reduced inequalities [14].

Additionally, this study makes a contribution to Goal 9: Industry, Innovation, and Infrastructure (OECD, 2020) through promoting advancements in applications of artificial intelligence within the sector of healthcare and building up infrastructures for digital healthcare research. These innovations are necessary for building health systems that are resilient enough to respond to the varying needs of diverse populations. Evidence from various scholars shows that artificial intelligence improves reliability as well as access to diagnostics and hence reduces health disparities among the vulnerable population [15]. This study seeks to create a more inclusive and sustainable healthcare framework that employs technology to provide high quality services across diverse healthcare environments. When implemented effectively to tackle global health concerns, these models could signify a substantial advancement towards a healthier and more equitable future.

Artificial intelligence networks and their branches will be explained in Section 2. Section 3 explains the previous studies, the methods used, and their results. A discussion of the results obtained from previous studies with comparison tables and the challenges they faced will be explained in Section 4. Future Directions and a Conclusion are given in Sections 5 and 6, respectively.

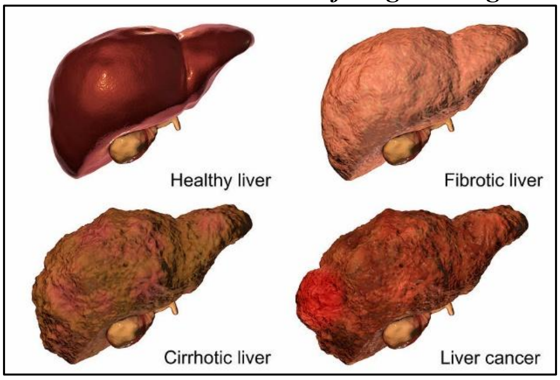

Fig. 1. The Stages of liver disease[16].

2. Artificial Neural Networks

Artificial neural networks (ANNs) have greatly enhanced the recognition of liver illnesses using medical imaging by increasing accuracy and enabling early detection[17]. These computational methods evaluate intricate imaging data to reveal subtle patterns essential for identifying conditions such as cirrhosis, liver fibrosis, and hepatocellular carcinoma (HCC). Artificial neural networks (ANNs) have improved the reliability and efficiency of diagnostic techniques in hepatology by combining modalities such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI). Artificial neural networks utilising ultrasound and MRI elastography data surpass conventional fibrosis staging techniques. These models can non-invasively and accurately detect liver tissue structure and metabolic alterations. Artificial neural networks analyse CT and MRI scans to identify early stage hepatocellular carcinoma (HCC) by distinguishing characteristics often missed by human evaluators[15]. This ability is crucial for timely intervention and improving patient outcomes. Neural networks have been employed to classify liver disease subtypes, such as non-alcoholic fatty liver disease (NAFLD) and viral hepatitis, enhancing diagnosis accuracy and enabling personalized treatment strategies[18].

The application of artificial neural networks in liver disease diagnostics, however promising, has numerous obstacles. The need for excellent, annotated datasets to teach models represents a significant limitation, since insufficient or biased datasets may undermine the models' reliability across diverse populations. Moreover, the inscrutable character of artificial neural networks hinders physicians' understanding of the reasoning behind predictions, thereby eroding trust in these tools. Ethical and regulatory issues, especially with patient privacy in the dissemination of imaging data, impede their acceptance[19]. Initiatives to tackle these difficulties involve the creation of explainable artificial intelligence (XAI) techniques, designed to enhance the transparency of the decision-making processes of artificial neural networks (ANNs). Furthermore, federated learning methodologies, which provide decentralized model training, are being investigated to maintain patient privacy while ensuring access to varied data sources. Prioritizing the integration of multimodal data encompassing imaging, genomic, and clinical information is essential for enhancing diagnostic robustness and model performance[20]. Artificial neural networks have pioneered a radical change in the diagnosis of hepatic pathologies through medical imaging by providing much more accurate, early, and non-invasive diagnostics[21]. The continued progress of AI and ethical standards offers much scope toward better patient outcomes and improved diagnostics for liver disease

2.1 Machine learning

The science of machine learning (ML) is a branch of artificial intelligence (AI) that allows systems to autonomously learn from data and enhance their performance over time, without explicit programming[22]. Rather than use explicit programming with preset rules for each case, machine learning (ML) systems learn and improve by discovering relationships and patterns in data. Unlike traditional programming that requires developers to give explicit instructions for every job[23], machine learning models are trained by using large datasets. Throughout the training process, these models examine the data to independently identify inherent patterns or connections. Upon completion of training, the models extrapolate from the acquired patterns to generate predictions or conclusions regarding novel, unobserved data. The ability to adapt and improve performance based on experience, without necessitating operator intervention for each new scenario, distinguishes machine learning from traditional programming methods[24].

By analyzing huge datasets and identifying patterns, machine learning models can generate predictions and make judgments based on the primary categories of machine learning supervised, unsupervised, and reinforcement training which differ in their approaches to data processing and knowledge acquisition. A primary use of machine learning in liver disease diagnostics is the assessment of fibrosis phases. Imaging techniques, like elastography and MRI, typically evaluate fibrosis, a gradual scarring of hepatic tissue[25]. machine learning algorithms are developed to assess data in liver stiffness images which can yield a very accurate and noninvasive diagnosis. Precise evaluation of stages of fibrosis is possible with machine learning models that pick out subtle changes in liver tissue over and above what traditional methods, such as liver biopsy, can achieve. Using machine learning models on CT and MRI images can aid in the early diagnosis of HCC for treatment purposes[26]. Machine learning algorithms may detect cancer size, form, and texture in liver imaging that are undetectable to humans, allowing for earlier and more accurate diagnosis. The chances of survival for liver tumors improve with early detection. In NAFLD and other chronic hepatic disorders, machine learning algorithms evaluate imaging data to ascertain prevalence and severity[27]. These algorithms categorize individuals for individualized treatment and monitor disease progression, thereby reducing the need for biopsies. Machine learning improves the detection of liver illness, increases efficiency, and facilitates early intervention, potentially saving lives by providing physicians with data driven decision-making insights. The presumed ML framework is depicted in Figure 2, Medical images are analyzed, features retrieved, models educated, and predictions tested for clinical applications.

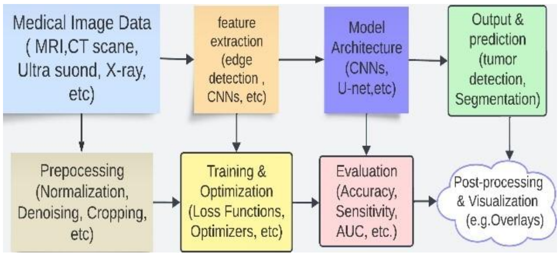

Fig. 2. The assumed machine-learning structure.

2.2 Deep Learning Models

As a branch of machine learning (ML), deep learning (DL) seeks to simulate how the human brain interprets data and recognizes patterns in order to aid in decision-making[27-28], Because of its complex design, which includes several hidden layers, it is known as a deep neural network (DNN)[30]. A multitude of studies has examined various approaches and concepts for analyzing images and deep learning in the detection of cancer[31]. The growing accessibility of extensive medical datasets, advanced computing systems, and GPUs positions deep learning algorithms as essential for disease identification in healthcare, especially in oncology. Deep learning competencies, including image segmentation, labelling, pattern recognition, and object detection, are considered optimal for radiology applications[32]. Deep learning methodologies are extensively employed in the detection, classification, and segmentation of tumours and lesions. A stacked ensemble model for automated disease diagnosis has been proposed in previous studies, combining bagged and boosted learners. DL techniques are widely used for tumor and lesion detection, classification, and image segmentation. Figure 2 presents a layered ensemble model for the automation of disease diagnosis.

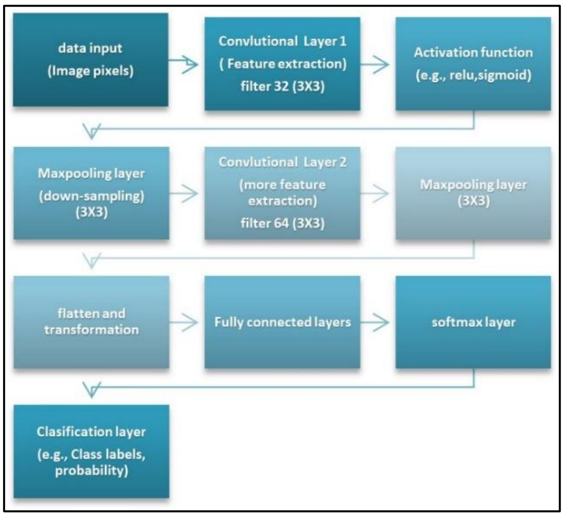

Fig. 3. an example of a model based on CNN architecture.

3. Literature Review

In 2017, Yugander et al. introduced a method for liver division of tumors in ambiguous CT images employing distance-regularized level set evolution (DRLSE) in conjunction with fuzzy C-means (FCM) clustering. The model comprises three principal phases: detection, processing, and pre-processing. FCM is employed for image segmentation subsequent to the application of a median filter to reduce noise in the CT images. The DRLSE method is employed to accurately define tumor margins. The dataset includes CT scans of patients with hepatocellular carcinoma from the Frederic National Laboratory for Cancer Research. To replicate real-world conditions, 10% and 15% salt-and-pepper noise were added to the images in the experiments. As evidence of the efficacy of the suggested approach, tumors were successfully removed from the warped pictures. One image portrayed a solitary tumor, whereas another represented four tumors. Particularly in the diagnosis of liver cancer, the suggested DRLSE model is important for enhancing the classification of noisy medical images. The results show the method's efficacy in tumor detection, which is crucial for liver cancer patients' treatment planning. The study acknowledges its limitations, such as its reliance on specific types of noise and the need for further validation across a range of datasets to enhance generalizability[7].

In 2018, Himmah et al. suggested a Watershed transform algorithm utilized in the segmentation process to identify liver regions by differentiating objects from the background in CT scan images. Subsequently, the image undergoes further segmentation through a binary threshold method to isolate the liver image as the target object. The final phase involves calculating the percentage of the affected area. The proposed algorithm was evaluated using a dataset comprising 150 axial CT scan images of the liver sourced from Hospital Haji Surabaya. The results demonstrated that the total liver segmentation attained a mean accuracy of 81.15%, whereas the segmentation of pathological regions attained a mean accuracy of 98.28%[6].

In 2018, Todoroki et al. developed a deep convolutional neural network to detect liver tumor candidates in CT images. This method's detection accuracy increased dramatically over earlier research. The study employs contrast-enhanced CT images to detect liver tumor candidates in three periods before and after contrast administration. K-means clustering, first-order statistical features, neural networks, Gaussian mixture models, expectation maximization and posterior marginal (EM/MPM) algorithms, and sigmoid edge models were employed. The proposed deep learning approach employs multilayered convolutional neural networks and performs well in image recognition and language processing. A deep CNN is used to estimate the probability of each liver pixel having a tumor after liver segmentation algorithms segment the CT picture. Deep learning is used to detect liver tumors in 3D multiphase contrast-enhanced CT scans of 75 patients. Cyst, focal nodular hyperplasia (FNH), Hepato cellular carcinoma (HCC), hemangioma (HEM), and metastases (METS) are in the dataset. The network output is the input patch's center pixel (target pixel) probability. The network outputs two neurons: one for non-tumor probability (0~1) and one for tumor probability (0~1). Learning accuracy is measured using a cross-entropy loss function. The experiment includes 225 CT volumes, 50 training samples (10 of each type), and 25 test cases (5 of each type). Created algorithms segregated the liver from each CT volume. Training samples are 48,000, and validation samples are 12,000. Most cancers were diagnosed by the DCNN approach, which outperformed the Bayesian model. Better detection results than the prior Bayesian model are in bold. Only HCC (PV phase) is lower than Bayesian[33].

In 2018, Adar et al. proposed the use of GANs in synthetic data augmentation to enhance liver lesion categorization from CT scans. Convolutional neural networks are limited in their performance due to a lack of annotated medical datasets, which this solves. Generative Adversarial Networks were utilized to generate high-quality pictures of liver lesions. Two architectures were employed: the Deep Convolutional GAN (DCGAN), which produced distinct lesion categories, and the Auxiliary Classifier GAN (ACGAN), which created labeled data for many categories concurrently. The research found that GAN-based synthetic data augmentation markedly enhances CNN performance by augmenting data variety. The produced data exhibited strong generalization, rendering it appropriate for analogous tasks in medical imaging. The main restriction identified was the utilization of 2D lesion pictures instead of 3D volumes, which might more effectively capture anatomical context. The necessity of training distinct GANs for each lesion category was emphasized as a disadvantage. A dataset of 182 annotated liver lesions, categorized as cysts, metastases, and hemangiomas, was employed. The integration of synthetic lesions generated by DCGAN led to a sensitivity increase to 85.7% and an improvement in specificity to 92.4%. The outcomes obtained using ACGAN were relatively subpar, although still above the baseline[34].

In 2018 Wang et al. argued in a proposal for transfer learning and fine-tuning the classification of liver lesion accuracy, especially when sample training is limited. The classification model makes use of a residual convolutional neural network (ResNet) that is one of the state-of-the-art networks for the classification of focal liver lesions from multiphase CT images. The dataset in use contains 388 multiphase CT images with 7 mm thickness each. Further, the dataset is partitioned into training (80%) and testing (20%) subsets. Experimental results revealed that fine-tuning enhances model accuracy and thus, in this case study, fine-tuning deep learning methodology was adopted to carry out the classification of focal liver lesions since unfounded data is among the challenges. This resulted in a fine-tuned increase in classification accuracy whereby it shot from 83.7% to 91.2%[35].

In 2019, Kang et al. presented a two-dimensional U-Net convolutional neural network for the fully automated segmentation of the liver from various imaging modalities and acquisition techniques utilized in clinical practice. The convolutional neural network underwent a two-stage training process.First, 300 SPGR MRI datasets without enhancements were used. Then, 30 CT datasets with and without enhancements, as well as hepatobiliary-phase T1-weighted MRI datasets, were transferred for transfer learning. Validation utilized internal and external datasets from 563 studies, yielding Dice scores of 0.94 for CT, 0.95 for hepatobiliary-phase T1-weighted MRI, and 0.92 for unenhanced SPGR MRI, demonstrating high segmentation accuracy. Liver volumetry and the measurement of the hepatic proton density fat fraction (PDFF) were used to assess the correctness of the model. Automated liver volumes demonstrated substantial concordance with manual measurements, exhibiting bias values of −58 mL for

CT and −89 mL for MR.I. PDFF measurements demonstrated substantial correlations, with mean biases consistently below 1%. The outcomes showed that automated segmentation was reliable for clinical applications, including volumetry, fat distribution, and liver morphological evaluation. The CNN's generalization was accomplished using minimal training data via transfer learning, which notably enhanced performance across datasets from diverse imaging techniques. Multimodal CNN segmentation accuracy showed significant enhancement for CT and hepatobiliary-phase MRI, with Dice score improvements of 0.12 and 0.87, respectively, relative to the initial model. The staged transfer-learning approach showed that accurate multimodal liver segmentation can be achieved without requiring large datasets[36].

In 2020, Dong et al. introduced the Hybridized Fully Convolutional Neural Network (HFCNN) to identify liver tumors. computational modeling has been utilized to tackle the ongoing issue of liver cancer. Every neural network experiences a training period succeeded by a testing phase. Throughout the training phase, the acquired CT data has been improved using several techniques known as data augmentation. A texture classifier has been created to distinguish regions of interest (ROIs) into benign and malignant liver lesions. The Dice seamlessness coefficient (DSC) functions as a standard metric for assessing the precision of automated or semi-automatic segmentation techniques. The dataset system, when utilized for image segmentation, has been evaluated, resulting in an average Dice Similarity Coefficient (DSC) of roughly 91%, signifying strong segmentation accuracy, alongside a false positive reduction rate of 92%[37].

In 2020, Jana et al. had proposed a novel method for the direct CT-based automatic prediction of non-alcoholic fatty liver disease (NAFLD) and NAFLD activity score (NAS) also determining the fibrosis stage based on CT data. Quite obviously, this method is noninvasive as opposed to the biopsy of livers and cheaper. Furthermore, they introduced a technique to use CT scan information combined with stained pathology data to increase the accuracy of NAS score and fibrosis stage predictions. The dataset used 30 subjects, each CT volumes and H&E-stained histopathology full image slides was one subject's CT volume and one subject's slide image. Although the Segmentation network achieved a Dice score of 0.9421 on test liver dataset, yet the prediction of NAS score appeared inadequate, with AUC ranging between 61.82 and 67.88[38].

In 2020, Almotairi et al. presented experimental research to adapt a deep learning model, originally developed for semantically segmenting objects in road image analysis, for segmenting tumors in DICOM-format CT liver images. SegNet, a modern encoder-decoder network architecture, was employed for this purpose. The encoder network employed the pre-trained VGG-16 image recognition model and utilized a corresponding decoded architecture to revert the extracted features to the image domain, facilitating pixel-wise classification. To facilitate the binary segmentation of medical images, a binary pixel classification layer was employed instead of the original classification layer. The VGG-16 pre-trained model was utilized for the encoder component of the network. Class weighting was utilized to equilibrate the dataset's groups, with the median frequency of class weights computed to improve training efficacy. Semantic segmentation was produced for input images during testing, yielding classification scores for each categorical label. The network was assessed utilizing individual photos from the test set. The suggested model was assessed utilizing the standard 3D-IRCADb-01 dataset, which consists of three-dimensional (3D) CT scans from 20 patients (10 females and 10 males), encompassing hepatic tumors in 15 cases, with a total of 2063 images available for training and testing. The design attained a tumor classification accuracy of as much as 99.9% in the learning phase[39].

In 2020, Lee et al. proposed a number of models for predicting for 5-year metachronous liver metastasis (5YLM) in patients with stage I-III colorectal cancer (CRC) to use convolutional neural networks (CNNs) to assess liver imaging data from preoperative abdominal CT imagesA retrospective analysis included a total of 2019 patients who underwent colectomy. Imaging features were extracted from CT scans, and subsequent principal component analysis (PCA) dimensionality reduction generated the principal components (PCs) used in modeling. Logistic regression and random forest classification were the modeling techniques used to build the predictive model, with integration of clinical features (age, sex, T stage, N stage) with extracted imaging data. The model integrating the first principal component (PC1) with clinical data exhibited superior predictive performance, attaining a mean area under the curve (AUC) of 0.747, in contrast to 0.709 for the model utilizing clinical features exclusively. PC1 demonstrated a strong association with 5YLM in multivariate analysis.The study found that the clinical data and imaging features, which were obtained through convolutional neural networks, improved the prognosis accuracy for patients having colorectal cancer with metachronous liver metastases. There was no evidence of liver metastasis at the time of initial colectomy; however, it was observed that imaging features derived from preoperative CT scans have predictive value concerning subsequent metastasis. Kaplan-Meier analysis showed a significant difference in 5YLM-free survival rates between low and high PC1 patients, at 89.6% and 95.9%, respectively. Further, there were significant associations of PC1 with several clinical parameters such as sex, BMI, alcohol use, and fatty liver condition[40].

In 2021, Wood et al. proposed an algorithm for liver CT segmentation based on deep learning and suggested that the segmented surfaces assist the fusion of images in applications such as guided needle placement procedures for the diagnosis and treatment of tumors in the liver. The former applied method was demonstrated in three clinical cases wherein, in each case, interventional CT was amicable to diagnostic CE-CT, PET/CT, and MRI image modalities for image guidance. This method for image segmentation was widely evaluated on the LiTS (Liver tumor challenge) segmentation dataset. The data, as provided, were composed of a total of 131 training datasets, and 70 were assigned to be test datasets. According to the findings of this application, the segmentation method that was developed is extremely accurate, as demonstrated by a Dice value of 96.1% out of seventy CT scans that were provided by the LiTS challenge. Therefore, the algorithm for segmentation was used to a collection of photographs that are associated with an intervention concerning liver tumors, in which the fusion is made on surfaces[41].

In 2021, Aghamohammadi et al. provided a novel method for separating liver and tumor in CT scans using a two-path convolutional neural network (TPCNN). The method was developed to solve problems including overlapping organs that are frequently observed in medical imaging, irregular shapes, and hazy boundaries.Three input representations a Z-score normalized picture, the original CT image, and an image encoded with the Local Direction of Gradient (LDOG) were employed to increase segmentation accuracy. Applying the Z-score normalization technique helped minimize noise and increase the ability to identify the liver from nearby organs. The LDOG method was used to encode structural and texture information, and it was able to capture important characteristics about the boundaries. A dual-path CNN design incorporated the preprocessing steps; this design retrieved semi-global features from bigger patches and local features from smaller ones. The network assigned weights to each pixel based on whether it was in the background, near a tumor, or near the liver. A stochastic gradient descent method was used to train the model, and dropout layers were included to reduce overfitting. The dataset utilized to evaluate the suggested approach consisted of 20,000 CT slices from 1,000 patients; we subsequently expanded the sample to 100,000 slices using data augmentation techniques. Performance was evaluated using metrics such as the Dice Similarity Coefficient (DICE), Relative Volume Difference (RVD), and Volume Overlap Error (VOE). For liver and tumor segmentation, the TPCNN outperformed seven well-known models, including DBN-DNN and EDCNN, with Dice scores of 92% and 95%, respectively. In spite of difficult conditions with overlapping organs, hazy borders, and tumors of various forms and textures, resiliency was demonstrated. The findings of the study showed that segmentation performance was significantly enhanced when utilizing multi-image inputs (Z-Score and LDOG)[42].

In 2021, Roy et al. created a convolutional autoencoder approach, termed (HistoCAE), for the segmentation of viable tumor regions in whole-slide liver histological pictures. The HistoCAE framework possesses a bifunctional design that amalgamates both supervised and unsupervised approaches. The autoencoder module reconstructs picture patches via dimensionality reduction while preserving spatial information, essential for recognizing structural features. A classifier module is subsequently utilized to distinguish tumor patches from non-tumor patches. A customized loss function that incorporates mean squared error (MSE), structural similarity (SSIM), and mean absolute error (MAE) was proposed, improving picture reconstruction accuracy and segmentation performance in contrast to typical autoencoders that rely solely on MSE loss. The suggested approach combined multi-resolution analysis, facilitating the segmentation of finer details in images taken at magnifications of 5×, 10×, and 20×. Various magnification patches were employed to enhance the model's sensitivity and precision. The MR-HistoCAE, an advanced multi-resolution variant, exhibited superior segmentation of tumor margins relative to the single-resolution HistoCAE.The model's ability to compress gigapixel images into feature mappings while keeping crucial information is impressive. The PAIP 2019 Challenge datasets include 50 precisely annotated whole slide images (WSIs) at 20× magnification. The images are divided into three groups: 70% for training, 20% for validation, and 10% for testing. classed as tumor or non-tumor based on a 30% coverage threshold. The proposed model was tested for recall, precision, F1-score, and dice matching. The experimental results showed that HistoCAE and Multi-Resolution (MR-HistoCAE) outperformed benchmark models such as ResNet-101 and U-Net, with the highest Dice identity value of 0.87[43].

In 2022, Prakash et al. presented a new approach termed Learning-based Disease Prediction Logic (LBDPL), which is derived from the conventional learning method known as Support Vector Machine (SVM). Standard methods such as the logistic regression (LR) algorithm, support vector machine (SVM), and k-nearest neighbor (kNN) method validate the LBDPL technique. The suggested methodology detects hepatic illness. This study focuses on predicting Non-Alcoholic Fatty Liver Disease (NAFLD) using machine learning techniques. This method involves processing the input image through stages such as image preprocessing, feature extraction, classification, and accuracy estimation. The datasets were sourced from Kaggle, containing around 560 patient records, both afflicted and unaffected, along with 65 included attributes. However, the time complexity is quite high when training the machine using liver MRI images. The digital image processing nature requires more time compared to the method of processing images and obtaining results. This method has a maximum prediction accuracy ratio of 98.9% for liver disease outcomes[44].

In the same year, Zhang et al. introduced a CNN algorithm for segmented CT images quantitatively assessed segmentation outcomes based on Dice similarity coefficient (DSC) and precision and recall metrics. Fifty-eight patients participated in this study, including 30 males; 28 females; their ages varied between 39 and 76, with a mean age of 57.5 ± 2.7 years, and all of them had liver tumors. The main purpose of the investigation was to assess the impact of applying the CNN algorithm for CT image segmentation of liver tumor patients. The resolution of the segmentation made through the CNN algorithm was compared with the segmentation made through holistically nested edge detection (HED) and U-Net algorithms. However, there was improvement presented by CNN algorithm segmentation in resolution and accuracy in contrast to images segmented by HED algorithm and U-Net algorithm. Additionally, their performance measures read as; DSC: 89.43%, precision: 95.74% and recall: 86.68%[45].

In 2023, Skwirczyński et al. proposed a protocol for liver monitoring. This entails categorizing the assessed patients into two groups: those with normal livers and those with tumors. The dataset comprises selections from 500 patients scanned using a 1.5 T MRI machine. Meticulous examination and enumeration of the lesions were conducted, comprising 145 cystic lesions (C), 126 hemangiomas (HM), 28 hepatocellular carcinomas (HCC), and 78 focal nodular hyperplasia's (FNH). The proposed technique may aid in diagnosing localized hepatic diseases and characterizing liver masses. Ultimately, each case is assigned a provisional diagnosis of either a normal liver or a liver with abnormalities. The AUC ROC is 0.925 (standard error 0.013, $p < 0.001$) for the training set and 0.852 (standard error 0.039, $p < 0.001$) for the test set. Sensitivity: 0.85; Specificity: 0.79[46].

In 2024, Song et al. presented a method for segmenting liver vessels using an enhanced 3D fully convolutional neural network V-Net. The original network structure was adjusted to the features of the liver vessels, and a pyramid-shaped convolution block was added between the network's decoding and encoding layers to enhance the network's ability to localize. Multi-resolution deep supervision was then added to the network to further enhance segmentation, and feature maps of various resolutions were fused to predict the networks as a whole segmentation outcome. This approach integrates two frequently utilized datasets. The LiTS17 comprises 201 cases of abdomen CT scans and served as the preliminary dataset. The second dataset is the Hepatic Vessel dataset, associated with the 2018 MICCAI. We have focused on the Dice similarity coefficient as our statistic of choice. This research analyzes the variation in experimental outcomes from ten-fold cross-validation evaluations concerning five distinct loss functions. The associated DSC values (DSC ± STD) were reported as 61.96% (±6.4), 68.47% (±5.7), 67.44% (±8.5), 71.19% (±7.3), and 72.53% (±5.9)[47].

In the same year, Kolli et al. introduced an advanced metaheuristic method termed Integrated Probabilistic Neural Network and Bayesian Optimizing (IPNN-BO). This approach seeks to improve dual probabilistic neural networks for liver tumor identification by employing natural metaheuristics. The technique includes several procedures: image acquisition, denoising, segmentation, and typing. The Integrated Probabilistic Neuronal Network with Bayesian Operations (IPNN-BO) was utilized to classify liver cancers in MRI datasets using dual convolutional neural networks. Furthermore, models including Naive Bayes and Markov chains were employed to assess the probability of possible disease occurrence. This probability outcome, together with other intrinsic characteristics, is regarded as supplementary input for network training. Experimental results are derived from preprocessed photos of the widely utilized LiTs17 dataset. IPNN-BO may attain an accuracy for validation of 99.25% with the implementation of Bayesian optimization, whereas KNN, CNN, and DCNN reach validation accuracies of 88%, 92.85%, and 93.75%, correspondingly[11].

4. Discussion and Challenges

The literature study demonstrates significant progress in the use of machine learning algorithms to diagnose liver disorders, particularly using modern imaging modalities such as MRI and CT scans[7]. The study established innovative techniques for dividing liver tumors, effectively addressing the challenges posed by noise in medical imaging. Fuzzy C-means clustering and distance-regularized level set evolution were combined to demonstrate a substantial enhancement in the accuracy of tumor detection[20]. With the advancement of research, deep learning models, such as the Embedded Fully Convoluted Neural Network (HFCNN)[37], have demonstrated exceptional performance metrics in the diagnosis of liver tumors.

Despite these advances, numerous challenges persist. Large, high-quality, and well-annotated datasets are difficult to obtain due to privacy concerns and annotation competence. Machine learning models can also be challenging to generalize due to imaging procedure diversity among healthcare organizations. Machine learning models have the ability to increase the accuracy of diagnoses, but they still can't replace the clinical judgment and sophisticated understanding of human medical professionals. This fact alone raises concerns about the practicality of machine learning results. Clinicians need to trust and understand these models' decision-making processes for them to be effectively used in their clinical work.

This work presents a comparison of the outcomes of machine learning and deep learning techniques employed in liver disease research during the past 9 years (refer to Table 1).

Table 1. A survey of the previous researches regarding ref. number, year, imaging modality, dataset, technique and results.

Author(s)	Year	Modality	Dataset	Algorithm/Method	Accuracy/Performance
Alahmer et al.[3]	2016	CT Images	60 patient case lesions	Classification Using Multiple ROIs	Accuracy 98.3% on multiple ROI features
Yugander et al.[7]	2017	Noisy CT Images	CIR dataset 2016	Fuzzy C-Means with Distance Regularized Level Set Evolution (DRLSE)	tumors are extracted from noisy abdominal CT scan image.
Yoshihiro Todoroki et al.[33]	2017	CT Images	75 cases of 3D multi-phase contrast-enhanced CT images of the liver	DCNN for Tumor Candidate Detection	The accuracy outperformed that of the Bayesian Model.
Himmah et al.[6]	2018	CT Images	150 axial CT scan images of the liver	Watershed Transform & Binary Thresholding	Accuracy: 98.28%
Adar et al.[34]	2018	CT images	182 annotated liver lesions	Generative Adversarial Networks (GANs) and Deep Convolutional GAN (DCGAN)	sensitivity 85.7% and specificity 92.4%.
Wang et al.[35]	2018	CT Images	388 multiphase CT images with 7 mm thickness	Residual convolutional neural network (ResNet)	accuracy whereby it shot from 83.7% to 91.2
Albishri et al.[9]	2019	CT Images	LiTS	Cascaded U-Net Model(CU-Net)	Dice: 89.4% (liver), 59.5% (tumor)
Vanmore et al.[48]	2019	CT Images	200 Patients Images	CNN-based Lesion Segmentation	Accuracy: 98.5%
Kang et al.[36]	2019	CT & MRI Images	300 SPGR MRI images with 30 Ct	Two-dimensional U-Net convolutional neural network	Dice scores of 0.94 for CT, 0.95 for hepatobiliary-phase T1-weighted MRI, and 0.92 for unenhanced SPGR MRI
Xia et al.[49]	2019	CT Images	LiTS Challenge	Improved DeepLab-v3	Dice score: 0.970
Lei et al.[50]	2019	CT Images	LiTS Challenge	Adversarial Densely Connected Network	Dice: 68.4% (tumor)

Srivastava et al.[10]	2020	CT & MRI Images	TCGA-LIHC dataset	Cuckoo Meta-heuristic with ML Algorithms	accuracy: 99.9%
Almotairi et al.[39]	2020	CT Images	3D-IRCADb-01 dataset	Modified SegNet contemporary encoder-decoder network)	Tumor Acc: 99.9%
Sangwoo Lee et al.[40]	2021	CT Images	2019 Patients (CRC)	CNN with Principal Component Analysis (PCA)	AUC: 0.747 (5YLM Prediction)
Aghamohammadi et al.[42]	2021	CT Images	1000 patient cases	Two-path CNN with Novel Encoding (TPCNN)	dice score for the tumour and liver altered from 90% to 95% and 85% to 92%
Fang et al.[41]	2021	CT Images	LiTS Challenge	Deep Learning with Fusion for Image Segmentation	Dice: 96.1%
Roy et al.[43]	2021	Histopathology Images	MICCAI 2019 Dataset	HistoCAE: Convolutional Autoencoder	Accuracy: 95.0%
Chen et al.[51]	2021	CT Images	LiTS, 4300 CT Images	Successive Encoder-Decoder (SED)	Dice: 92% (liver), 75% (tumor)
Chi et al.[52]	2021	CT Images	MICCAI 2017, 3DIRCADb	X-Net (Multi-branch U-Net)	Dice : 84.3%
Ghazal et al.[53]	2022	Patient Data	dataset of 65532sets of records	KNN, SVM, DL	Accuracy: 88.4%
Prakash et al.[44]	2022	MRI Images	560 Kaggle dataset	Learning based Disease Prediction Logic (LBDPL)	Accuracy: 98.9%
Laddha et al.[54]	2023	MRI Images	kaggle dataset	Histogram of Oriented Gradients (HOG) with Random Forest	Accuracy:91.67%
Jiajun Lu [55]	2023	Clinical Data	Indian Liver Patient Dataset	Random Forest	Accuracy: 73.56%
Kasipandi et al.[56]	2024	CT Images	IRCADB01	Mask R-CNN with Swin Transformer Network	Accuracy: 99.23%
Dashti et al.[57]	2024	Patient Data	ILDP	Multilayer Perceptron Neural Network	Accuracy: 99.5%
Song et al.[47]	2024	CT Images	LiTS17 with 2018 MICCAI challenge	3D V-Net with Multi-resolution Deep Supervision	Dice Improved
Malik et al.[58]	2024	CT Images	1200 patient images	Enhanced Multi-Class Liver Tumor Identification (EMLTI)	ML: 99.7%, DL: 78%-97%
Kolli et al.[11]	2024	CT Images	LiTS17	Probabilistic Neural Network with Bayesian Optimization	Accuracy: 99.25%

Table 2 and Figure 4 shows how deep learning techniques appear to be growing and becoming better than machine learning, how academics are adopting them, and how accurate their findings are as a result. The data were acquired via a systematic literature review methodology to guarantee the thorough and impartial collecting of pertinent studies. The stages of advancement in machine learning and deep learning applications during the previous nine years were determined through a methodical analysis of articles, with results refined according to precise inclusion and exclusion criteria. The area may not be fully understood by this narrow perspective, which also might not include all pertinent advancements in deep learning techniques used to liver research.

Table 2. demonstrates the apparent rise of machine learning and deep learning techniques.

Year	Number of ML Papers	Number of DL Papers	Total Papers	Algorithms and models used
2016	20	10	30	Early CNNs, SVM, Random Forest; liver lesion classification.
2017	35	25	60	U-Net for segmentation; initial transfer learning approaches.
2018	50	45	95	Growth of ResNet/DenseNet; GANs for data augmentation; HCC classification.
2019	60	60	120	3D CNNs for volumetric imaging; multi-task learning; liver fibrosis detection.
2020	75	80	155	Attention mechanisms in segmentation; hybrid ML/DL models; fatty liver detection.
2021	100	120	220	GANs for liver tumor segmentation; ensemble approaches; small dataset solutions.
2022	120	140	260	Multi-modal imaging; advanced U-Net variants; liver lesion segmentation.
2023	150	180	330	3D U-Net; Transformer models; HCC segmentation; fibrosis staging.
2024	160	200	360	Generative models for liver data; multi-center clinical applications.

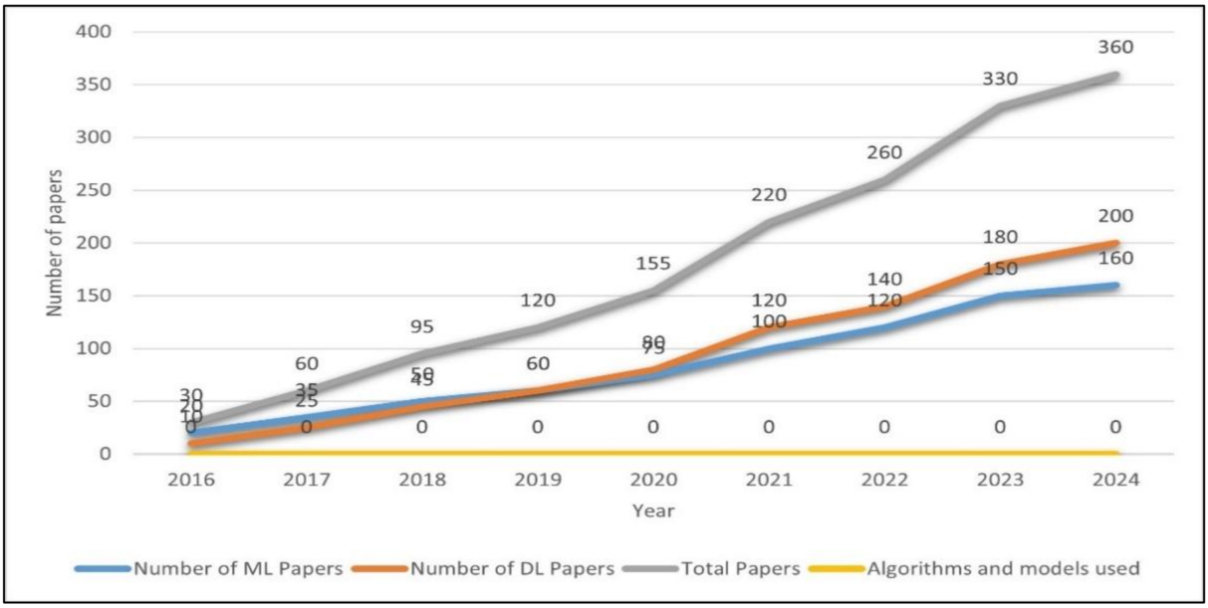

Fig. 4. The growth stages of machine learning and deep learning applications over the past 9 years.

5. Future Directions

Future research should focus on validating machine learning models across varied datasets and clinical settings to improve their robustness and applicability. This entails the necessity for standardized imaging techniques to provide uniformity in data inputs, which is essential for training efficient models. Furthermore, there is an urgent necessity to formulate solutions for enhancing current datasets, such as utilizing data synthesis methods or transfer learning, to alleviate the difficulties associated with insufficient annotated data. Integrating clinical expertise with machine learning algorithms is crucial for enhancing the interpretability of these models, enabling physicians to comprehend the reasoning behind model predictions. Collaboration between data scientists and medical practitioners will be vital in improving these algorithms and assuring that they are appropriate for clinical workflows. Hybrid models, which refer to the combination of classical machine learning practices with deep learning approaches, might also develop favorable environments toward enhancing diagnosis much more accurately and powerfully. Advanced machine learning in liver disease diagnosis therefore demands the creation of multi-disciplinary collaborations underpinned by practical relevance.

6. Conclusion

The review sets the use of machine learning methods in the broader context of changes around liver disease detection with particular reference to new sophisticated imaging tools. The changes described in this paper reflect a clear departure from conventional modes of diagnosis toward data-driven methodologies that could greatly enhance the planning of treatment and diagnosis. However, there are still numerous obstacles that prevent these advancements from being fully implemented in reality. These include issues like the requirement for comprehensible machine learning outcomes, consistency in imaging methodologies, and high-quality datasets. More validation work in different clinical situations and with the infusion of clinical expertise is needed as the area of liver disease detection keeps evolving. The health sector will maximize the benefits associated with the use of machine learning not only for improved patient outcomes but also in hastening the process of diagnosis, which shall benefit advanced strategies for treating liver diseases.

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