Computer Vision and Deep Learning for Liver Disease Diagnosis: A Systematic Review

[1] Raad W. Salah,[2] Ielaf O. AbdulMajjed

[1,2] Computer Science Department, University of Mosul, Mosul, Iraq.

Abstract:

Liver diseases remain a major global health concern, posing significant diagnostic challenges due to their complex and heterogeneous nature. Conventional diagnostic methods rely heavily on clinical expertise and subjective interpretation, which can lead to variability and error. With recent advancements in artificial intelligence (AI), particularly in computer vision and deep learning (DL), there is a growing opportunity to improve the accuracy and efficiency of liver disease diagnosis. This review explores the applications of computer vision in the medical imaging analysis of liver diseases, including key processes such as image preprocessing, segmentation, lesion detection, and disease classification. The study also discusses the limitations of current techniques, critical challenges including data quality, model interpretability, and privacy, as well as emerging research directions. The integration of computer vision into clinical workflows holds great promise for enhancing early diagnosis, supporting clinical decision-making, and ultimately improving patient outcomes.

Keywords: Computer vision (CV), Artificial intelligence (AI), Liver Disease, Machine Learning (ML), Deep Learning (DL), NAFLD, ALD.

1. Introduction:

It may be possible to save lives with an early diagnosis. Even the most experienced medical professional cannot identify certain disorders, yet they can be identified in their early stages. A patient's life expectancy can be significantly increased by early diagnosis (Sontakke& Dani, 2017). Clinicians use a wide range of diagnostic data modalities to diagnose diseases, predict how those diseases will progress, and suggest the best

course of therapy, Computer vision methods, especially those that use deep learning (DL) and machine learning (ML) have recently demonstrated encouraging outcomes in improving and automating the diagnosis of liver illness (Tomašev et al., 2019). Computers can now learn from large, complicated datasets and address practical issues in and outside of the medical field thanks to artificial intelligence (AI), which produces results that are on par with or better than those of humans. This study reviews how computer vision is used to diagnose liver disease, focusing on important technologies such as image preprocessing, liver segmentation, lesion detection, and liver pathology categorization. A more modern implementation of this method that uses numerous layers is called deep learning (DL), which works best with large amounts of complex or

highly dimensional data. The use of deep learning (DL) has recently increased due to increased computational power and the size of available healthcare datasets. This review investigates the application of computer vision technologies in liver disease diagnosis, focusing on the pertinent automated technologies and their use in medicine (Ahn et al., 2021) The figure (1) shows an overview of many of AI applications that are used in addressing liver diseases and figure (2) the development in using computer vision.

1.1 Problem Statement

Despite the advancement of medical imaging technologies, liver disease diagnosis continues to suffer from inaccuracy, operator-dependence, and limited early detection. Current diagnostic tools are not always sufficient to handle the complexity of liver conditions. Therefore, there is a need for intelligent, automated approaches that can support clinicians and enhance diagnostic reliability.

1.2 Significance of The Study

This review is significant because it explores how computer vision and artificial intelligence can address the limitations of conventional diagnostic methods. It highlights state-of-the-art models and techniques, identifies current gaps, and proposes directions for future research that can contribute to more accurate and accessible liver disease diagnosis.
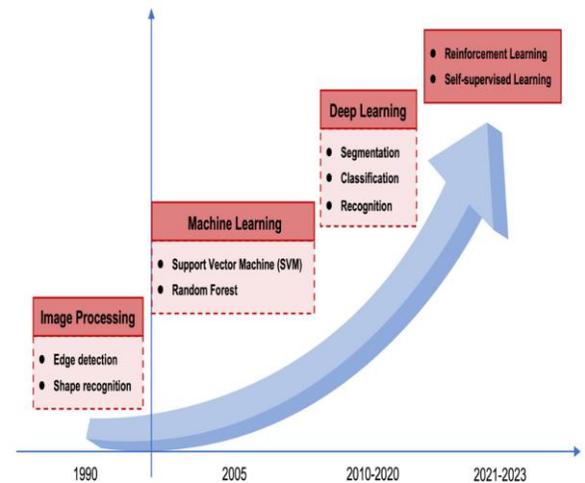

Figure 1. Overview of the applications of AI in addressing liver damage (Hunter, 2019)

Figure 2. The development of liver disease computer vision analysis.

2. Liver Diseases

From moderate illnesses like non-alcoholic fatty liver disease (NAFLD) to severe problems like liver fibrosis, cirrhosis, and liver cancer, liver diseases cover a wide variety of ailments. Although the symptoms of some illnesses may be similar, the therapies needed are often different. A precise and timely diagnosis is necessary for a successful intervention. Globally.

● NAFLD

Nonalcoholic fatty liver disease (NAFLD) is becoming the most common chronic liver disease. An estimated one billion people worldwide suffer from NAFLD, which may affect about 25% of the global population. NAFLD is generally divided into two subtypes: the progressive form of NAFLD, known as NASH, and the non-progressive form, known as nonalcoholic fatty liver disease (NAFL), shown in the figure (3) below (Loomba et al., 2021) Nonetheless, there is a degree of pleiotropy in immune-related loci linked to NAFLD and NASH, which can affect different phenotypes like sepsis or premature birth. Lastly, they concentrate on using the present genetic understanding of NAFLD
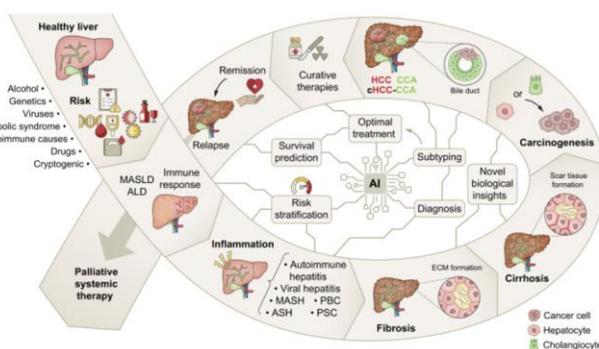
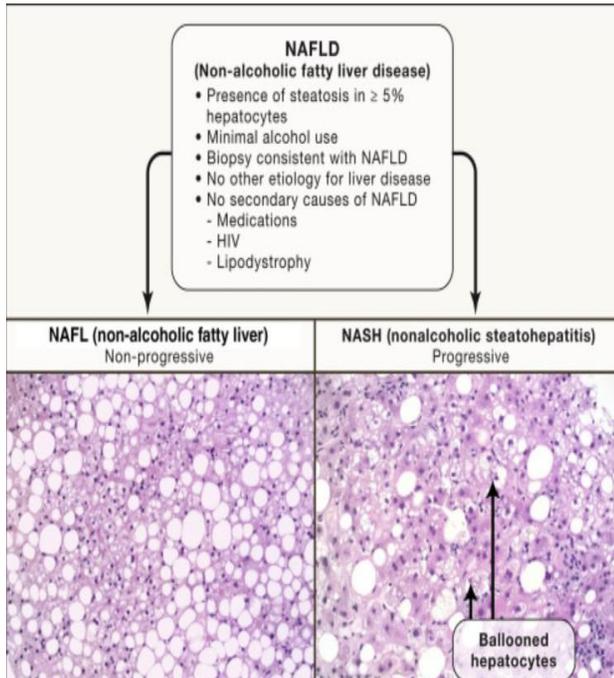and NASH to precision therapy (Sookoian & Pirola, 2019).

Figure 3. The histologic distinction between NASH and NAFLD (Loomba et al., 2021)

- ALD

The most common kind of chronic liver disease in the world is alcoholic liver disease (ALD). Unlike viral hepatitis, which can be diagnosed through objective testing, ALD is reliant on people's self-report of alcohol consumption, making precise estimates of the condition challenging to ascertain. Based on a number of indications, the burden of ALD is predicted to rise. Reducing alcohol consumption is ultimately necessary to lessen the burden of ALD Hepatic inflammation is a hallmark of alcoholic steatohepatitis (ASH), which can develop from alcoholic fatty liver (AFL) (Cheemerla & Balakrishnan, 2021).

- Hepatitis

A group of viral infections (Hepatitis A, B, C) that can lead to chronic liver disease and cirrhosis, figure (4)

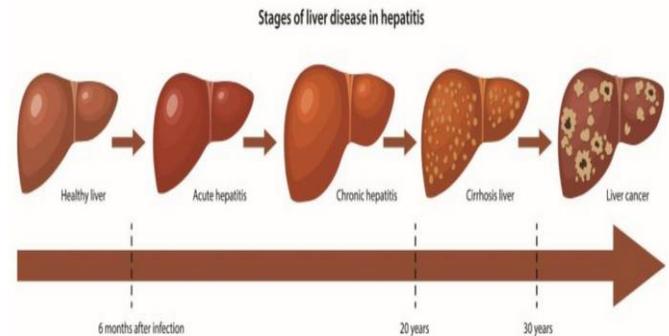illustrates the stages of liver diseases in hepatitis (Kim & Kim, 2017).

Figure 4. Stages of liver disease in hepatitis (Kim & Kim, 2017).

- Liver Cancer

Is frequently brought on by chronic liver illness, particularly cirrhosis or hepatitis. Hepatocellular carcinoma, or primary liver cancer, as well as metastases from other tumors in the body are included (Cotter & Rinella, 2020).

— Hemochromatosis: It is a hereditary disorder that damages the liver and other organs by causing the body to accumulate iron excessively (Asrani et al., 2019).

— Cirrhosis: Long-term liver injury causes scarring of the liver tissue, which reduces liver function. Many illnesses, such as fatty liver disease, viral hepatitis, and persistent alcohol consumption, can cause it (Powell et al., 2021).

— Wilson's disease: A hereditary condition where copper builds up in the liver, causing harm to the liver and other organs (Castera et al., 2019).

— Liver Failure: A disease in which the liver cannot carry out its vital tasks, resulting in infections, hemorrhage, and organ failure (Lonardo et al., 2020).

3. Common Liver Disease Diagnosis Methods

Testing The following are typical techniques for diagnosing liver diseases:

i. Ultrasound Imaging: This non-invasive technique is widely used for liver imaging.

ii. High-resolution images are produced using magnetic resonance imaging (MRI), which helps identify liver fibrosis and malignancies.

iii. Computed Tomography (CT): Used to assess metastases and liver lesions.

The gold standard, a biopsy, is intrusive and prone to sample errors (Kaya & Yilmaz, 2021).

4. Computer Vision Methods for Diagnosing Liver Disease:

Data collection, cleaning, transformation, reduction, model construction, evaluation, and performance evaluation are all part of the current process for creating AI and big data-based predictive models for liver diagnosis, all of which are necessary to develop accurate and successful prediction models. The main computer vision techniques used to diagnose liver disease are covered in this section (Singh et al., 2020).

4.1 Data Acquisition

The starting point of liver disease predictive modeling is data collection. The quantity and quality of the data have a significant impact on how well AI systems function. The following data sources are frequently used to forecast liver disease:

1) EHRs, or electronic health records: EHRs include comprehensive patient information, including demographics, medical history, test findings, prescription history, and imaging studies. They offer cohort data that can be used to evaluate the onset of disease and the effectiveness of treatments (Kaur et al., 2020).

2) Data from Medical Imaging: All of the diagnostic methods listed above help identify liver conditions like tumors, liver fibrosis, and cirrhosis. To detect and classify liver diseases, these pictures are fed into DL models like the CNN (Lu et al., 2024).

3) Genetic and Proteomic Data: This is particularly true in light of recent advancements in precision medicine, which integrate genetic and proteomic data to create prediction models. Gene expression profiles

4.2 Image Processing

Medical images can be noisy or low in resolution, hence image preprocessing is essential to enhancing their quality. To make sure that later algorithms can extract pertinent features from the images, methods including image normalization, denoising, contrast augmentation, and histotrophic equalization are frequently used (Brattain et al., 2020). This stage includes many steps:

- Data Cleaning: This comprises eradicating or altering erroneous entries, addressing the missing values, and excluding observation values that may lead to altered model findings. Lack of data can be solved by approaches such as mean imputation, K-Nearest Neighbor imputation, or even complex methods like multiple imputations (Zhou et al., 2019).

- Data Normalization and Scaling: Normalization methods like as Z-score normalization or Min-Max scaling are applied to numerical data where features must be standardized before being employed by algorithms like SVM and neural networks that are impacted by feature ranges (Wu et al., 2019).

- Data anonymization is used to protect patient information while allowing the data to be utilized for model training because health records are considered sensitive. Scrubbing out personally identifiable information (PII) and implementing de-identification

processes are examples of such safeguards (Zhou et al., 2019).

4.3 Image Segmentation

The segmentation stage of the image after it has been labeled, in which the NET_U network was used with 50_Resnet. The NET_U network extracts image features and consists of two paths. The first path is the contraction path, also known as the encoder or analysis path, which is similar to a regular convolution network and provides classification information. The second path is the expansion path, also known as the decoder or synthesis path, and consists of ascending convolutions and sequences with features from the contraction path. This expansion allows the network to learn classification information.

The Residual Network (ResNet) was created in 2016 by a group of academics (Li et al., 2022). ResNet is a useful framework for CNNs. It was discovered that it might find an innovative solution to the vanishing gradient problem by using the "identity shortcut connection," which enables any levels to be bypassed by extracting activation through one layer and feeding it to another layer. ResNet is a real deep network that was exhibited in the challenge with 152 layers. According to the observations, the network depth is directly proportional to the saturation of accuracy, while after that point, it starts to get corrupted rapidly and the Vanishing Gradient Problem is needed to be resolved by network team.

Similar to recent studies that enhance image quality through optimization algorithms, such as the Firefly Algorithm used to improve multi-focus image fusion via anisotropic diffusion and bilateral filtering (Ghazal & Dahl, 2025), preprocessing techniques play a critical role in obtaining clearer and more informative medical images before segmentation or classification (Masood, 2017).

Accurate liver segmentation is essential because it separates the liver from surrounding tissues for additional examination. The following are some methods for liver segmentation:

— Thresholding: A straightforward yet efficient method for detecting liver in contrast-enhanced images. The Region-Based Segmentation grows from seed locations to the borders of the segment liver.

— Deep Learning-Based Segmentation: The liver segmentation procedure has been automated using convolutional neural networks (CNNs) and U-Net architectures, which have produced good accuracy in both CT and MRI scans (Gul et al., 2022).

4.4 Lesion Detection

Because liver lesions can differ in size, shape, and texture, it might be difficult to detect tumors, cysts, and fatty liver regions. The following are some computer vision methods for detecting lesions:

a. Edge Detection: Techniques such as the Canny edge detector aid in locating the limits of lesions (Nayantara et al., 2020).

b. CNNs for Tumor Detection: By using deep feature learning, CNNs have demonstrated remarkable efficacy in identifying liver cancers, including hepatocellular carcinoma (Kumar et al., 2021).

c. Multi-scale Analysis: Lesions of different sizes can be found by utilizing various image scales (Ambade et al., 2019).

4.5 Classification of Diseases and Forecasting Prognoses

convolutional neural networks (CNN) have become one of the deep learning techniques that has been used in fingerprint recognition due to their analytical robustness and feature extraction capabilities, which allow a significant number of computations to be executed on a single region of an image (Galala, 2023). Integrating locally connected layers for feature extraction and fully interconnected layers for classification is the key to the model's success. The convolution layers use filters like 'blur,' 'sharpen,' and 'edge-detection' to slide the filter across the input image and generate an output feature map. The deeper layers generate more complex and sophisticated features by integrating the output of the previous layers using a non-linear function in order to capture.

Computer vision systems can categorize liver illnesses using extracted attributes when pertinent locations (such as liver tissue or lesions) have been recognized. Liver conditions can be categorized using machine learning algorithms including support vector machines (SVM), random forests, and deep learning models. Notably, CNNs have outperformed other algorithms in automatically identifying liver disorders from imaging data, including cirrhosis and fibrosis.

Additionally, by examining longitudinal picture datasets, computer vision algorithms can also be utilized to forecast the course of liver disease. For instance, automated methods can be used to quantify the degree of liver fibrosis using MRI or ultrasound pictures (Nam et al., 2022). Figure (5) shows image analysis workflow.
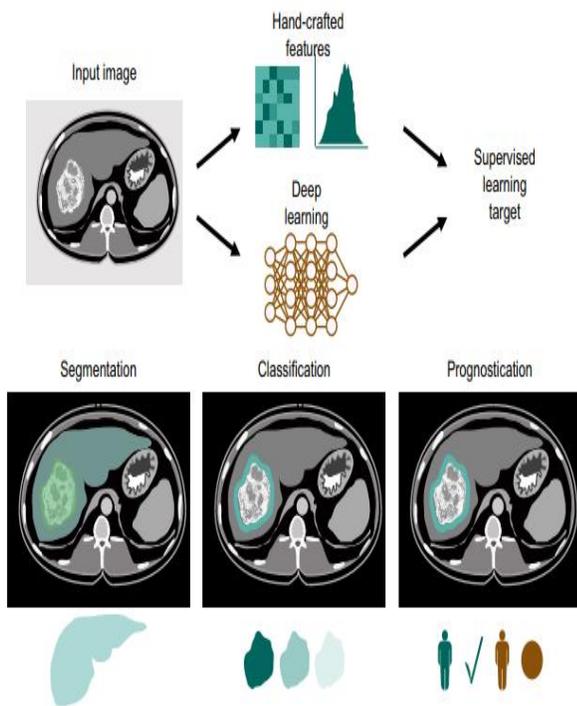

Figure 5. Image analysis workflow (Ali, 2024)

5. Methodology of The Review

This review study followed a structured approach to identify, select, and analyze relevant research articles related to the use of computer vision techniques in liver disease diagnosis.

Research articles published between 2017 and 2024 were gathered from reputable databases including PubMed, Scopus, IEEE Xplore, and Google Scholar. The search was conducted using the following keywords and their combinations: "liver disease", "computer vision", "deep learning", "medical imaging", "segmentation", and "classification".

6. Related Work

Table 1. Related Work

Ref. No	Year	Method	Result
(Rahman et al., 2019)	2019	Logistic Regression, K Nearest Neighbors, Decision Tree, Support Vector Machine, Naïve Bayes, and Random Forest.	accuracy of models (75%, 74%, 69%, 64%, 62% and 53%) for LR, RF, DT, SVM, KNN and NB.
(Shaheamlung & Kaur, 2021)	2020	a hybrid classification method	accuracy =77.58%
(Afrin et al., 2021)	2021	DT	accuracy =94.295%
(Hossen et al., 2022)	2022	(DT), (LR), (MLP), (ANN), (RF), (KNN)	accuracy of models (72.89%, 81.32%, 60.24%, 86.14%, 75.61%, and 65.52%.)
(Anter & Abualigah, 2023)	2023	CNN	accuracy =90%
(Montazeri & Montazeri, 2024)	2024	Naïve Bayes, Trees Random Forest, KNN, AdaBoost, SVM	accuracy of models (55%, 72%, 64%, 70% and 71%)

7. Difficulties and Restrictions

Despite computer vision's huge promise for liver disease diagnosis, there are a number of obstacles that need to be overcome:

- Data Availability and Quality: Low resolution, missing annotations, and excessive noise levels are common issues with medical imaging data that might impact model performance.

- Generalization: In real-world clinical situations, models that have been trained on particular datasets could not generalize well to other datasets.

- Interpretability: A common perception of deep learning models is that they are "black boxes." Their broad use in medical practice, where comprehending the reasoning behind predictions is essential, may be hampered by their lack of interpretability.

- Data Privacy: Using patient data presents privacy and security issues that necessitate following laws and ethical guidelines like HIPAA (Mosquera et al., 2023).

8. Challenges and Limitations

While there is potential promise, there are still issues to work on:

- The Annotation Problem: There is sparse low-resolution and noisy annotated data.

- Underperformance: Models that are trained on particular datasets tend to overfit to them, as they perform poorly.

- Lack of Trust: The transparency of DL models is rather low.

- Ethics: There are concerns of ethics when it comes to the usage of patient data.

9. Future Directions to Improve Outcomes

- Ultrasonography: Data acquired from MRI and CT scans are put to further use when performed on ultrasound.

- Collaborative Training: This type of training protects privacy.

- AI Authoring: AI aids in the authors and thus improves the clinician's trust.

10. Conclusion

The integration of artificial intelligence and computer vision has revolutionized the diagnosis of liver diseases by offering tools that can assist clinicians with accurate, efficient, and early detection. Through various techniques like segmentation, lesion detection, and disease classification, computer vision algorithms—especially deep learning-based models—have demonstrated strong potential in identifying liver abnormalities with high precision.

Despite these advancements, several challenges remain, such as limited availability of high-quality annotated datasets, concerns over model interpretability, and the need for robust validation in clinical settings. Addressing data privacy, regulatory concerns, and physician trust is essential for these technologies to move from research to routine medical practice.

Future efforts should focus on building explainable AI models, increasing dataset diversity, and ensuring cross-institutional collaboration to enable large-scale deployment. Ultimately, a synergistic relationship between AI systems and healthcare professionals is necessary to maximize the benefits of these technologies in liver disease management.

References

Afrin, S., Shamrat, F. J. M., Nibir, T. I., Muntasim, M. F., Moharram, M. S., Imran, M. M., & Abdulla, M. (2021). Supervised machine learning based liver disease prediction approach with LASSO feature selection. Bulletin of Electrical Engineering and Informatics.

Ahn, J. C., Connell, A., Simonetto, D. A., Hughes, C., & Shah, V. H. (2021). Application of artificial intelligence for the diagnosis and treatment of liver diseases. Hepatology, 73(6), 2546–2563.

Ali, A. M. A. A. (2024). A comprehensive review of liver disease prediction using big and artificial intelligence.

Ambade, A., Lowe, P., Kodys, K., Catalano, D., Gyongyosi, B., Cho, Y., ... & Szabo, G. (2019). Pharmacological inhibition of CCR2/5 signaling prevents and reverses alcohol-induced liver damage, steatosis, and inflammation in mice. Hepatology, 69(3), 1105–1119.

Anter, A. M., & Abualigah, L. (2023). Deep federated machine learning-based optimization methods for liver tumor diagnosis: A review. Archives of Computational Methods in Engineering, 30(5), 3359–3378.

Asrani, S. K., Devarbhavi, H., Eaton, J., & Kamath, P. S. (2019). Burden of liver diseases in the world. Journal of Hepatology, 70(1), 151–171.

Brattain, L. J., Ozturk, A., Telfer, B. A., Dhyani, M., Grajo, J. R., & Samir, A. E. (2020). Image processing pipeline for liver fibrosis classification using ultrasound shear wave elastography. Ultrasound in Medicine & Biology, 46(10), 2667–2676.

Castera, L., Friedrich-Rust, M., & Loomba, R. (2019). Noninvasive assessment of liver disease in patients with nonalcoholic fatty liver disease. Gastroenterology, 156(5), 1264–1281.

Cheemerla, S., & Balakrishnan, M. (2021). Global epidemiology of chronic liver disease. Clinical Liver Disease, 17(5), 365–370.

Cotter, T. G., & Rinella, M. (2020). Nonalcoholic fatty liver disease 2020: The state of the disease. Gastroenterology, 158(7), 1851–1864.

Ghazal, K. M., & Dahl, I. O. A. M. (2025). Applying the firefly algorithm to enhance the outcomes of multi-focus image fusion through anisotropic diffusion filters and bilateral filtering (ABF). AIP Conference Proceedings, 3264, 030009. https://doi.org/10.1063/5.0260508

Gul, S., Khan, M. S., Bibi, A., Khandakar, A., Ayari, M. A., & Chowdhury, M. E. (2022). Deep learning techniques for liver and liver tumor segmentation: A review. Computers in Biology and Medicine, 147, 105620.

Haleem, A., Ben Jabra, S., & Chainbi, W. (2025). Biometric fingerprint identification in low-quality samples using a hybrid features extraction method with deep learning. Evolving Systems, 16, 94. https://doi.org/10.1007/s12530-025-09726-5

Hoang, V. A., Nguyen, D. T., Bui, H. T., Le, T. L., Vu, D. H., Tran, B. G., ... & Vu, H. (2023, December). Comprehensive study of liver disease prediction using machine learning. In 2023 1st International Conference on Health Science and Technology (ICHST).

Hunter, S. (2019, March 18). What causes cirrhosis? News-Medical. Retrieved April 14, 2025, from https://www.news-medical.net/health/What-Causes-Cirrhosis.aspx

Hossen, M. S., Haque, I., Sarkar, P. R., Islam, M. A., Fahim, W. A., & Khatun, T. (2022, June). Examining the risk factors of liver disease: A machine learning approach. In 2022 7th International Conference on Communication and Electronics Systems (ICCES).

Kaur, S., Singla, J., Nkenyereye, L., Jha, S., Prashar, D., Joshi, G. P., ... & Islam, S. R. (2020). Medical diagnostic systems using artificial intelligence (AI) algorithms: Principles and perspectives. IEEE Access, 8, 228049–228069.

Kaya, E., & Yilmaz, Y. (2021). Metabolic-associated fatty liver disease (MAFLD): A multi-systemic disease beyond the liver. Journal of Clinical and Translational Hepatology, 10(2), 329.

Kim, D., & Kim, W. R. (2017). Nonobese fatty liver disease. Clinical Gastroenterology and Hepatology, 15(4), 474–485.

Kumar, S., Dhir, R., & Chaurasia, N. (2021, March). Brain tumor detection analysis using CNN: A review. In 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) (pp. 1061–1067). IEEE.

Li, Y., Wang, X., Zhang, J., Zhang, S., & Jiao, J. (2022). Applications of artificial intelligence (AI) in researches on non-alcoholic fatty liver disease (NAFLD): A systematic review. Reviews in Endocrine and Metabolic Disorders, 23(3), 387–400.

Lonardo, A., Leoni, S., Alswat, K. A., & Fouad, Y. (2020). History of nonalcoholic fatty liver disease. International Journal of Molecular Sciences, 21(16), 5888.

Loomba, R., Friedman, S. L., & Shulman, G. I. (2021). Mechanisms and disease consequences of nonalcoholic fatty liver disease. Cell, 184(10), 2537–2564.

Lu, F., Meng, Y., Song, X., Li, X., Liu, Z., Gu, C., ... & Qi, X. (2024). Artificial intelligence in liver diseases: Recent advances. Advances in Therapy, 41(3), 967–990.

Montazeri, M., & Montazeri, M. (2024). Machine learning models for predicting the diagnosis of liver disease. Koomesh, 16(1), 53–59.

Mosquera, C., Lara, M. A. R., Díaz, F. N., Binder, F., & Benitez, S. E. (2023). Introducing computer vision into healthcare workflows. In Digital Health: From Assumptions to Implementations (pp. 43–62). Cham: Springer International Publishing.

Nam, D., Chapiro, J., Paradis, V., Seraphin, T. P., & Kather, J. N. (2022). Artificial intelligence in liver diseases: Improving diagnostics, prognostics, and response prediction. JHEP Reports, 4(4), 100443.

Najeeb, R. S. M., & Abdul Majjed, I. O. (2022). Brain tumor segmentation utilizing generative adversarial, ResNet, and U-Net deep learning. In Proceedings of the 8th International Conference on Contemporary Information Technology and Mathematics (ICCITM 2022), University of Mosul, Iraq.

Najeeb, R. S. M. (2023). 3D reconstruction of X-ray images from 2D images [Master's thesis, University of Mosul]. University of Mosul Repository.

Nayantara, P. V., Kamath, S., Manjunath, K. N., & Rajagopal, K. V. (2020). Computer-aided diagnosis of liver lesions using CT images: A systematic review. Computers in Biology and Medicine, 127, 104035.

Powell, E. E., Wong, V. W. S., & Rinella, M. (2021). Non-alcoholic fatty liver disease. The Lancet, 397(10290), 2212–2224.

Rahman, A. S., Shamrat, F. J. M., Tasnim, Z., Roy, J., & Hossain, S. A. (2019). A comparative study on liver disease prediction using supervised machine learning algorithms. International Journal of Scientific & Technology Research, 8(11), 419–422.

Raghad, S. M. N. (2023). 3D reconstruction of X-ray images from 2D images [Master's thesis, University of Mosul]. University of Mosul Repository.

Shaheamlung, G., & Kaur, H. (2021). The diagnosis of chronic liver disease using machine learning techniques. Information Technology in Industry, 9(2), 554–564.

Singh, J., Bagga, S., & Kaur, R. (2020). Software-based prediction of liver disease with feature selection and classification techniques. Procedia Computer Science, 167, 1970–1980.

Sookoian, S., & Pirola, C. J. (2019, May). Genetics of nonalcoholic fatty liver disease: From pathogenesis to therapeutics. In Seminars in Liver Disease (Vol. 39, No. 02, pp. 124–140). Thieme Medical Publishers.

Sontakke, S., Lohokare, J., & Dani, R. (2017). Diagnosis of liver diseases using machine learning. In 2017 International Conference on Emerging Trends & Innovation in ICT (ICEI) (pp. 129–133). IEEE. https://doi.org/10.1109/ETIICT.2017.7977023

Tomašev, N., Glorot, X., Rae, J. W., Zielinski, M., Askham, H., Saraiva, A., ... & Mohamed, S. (2019). A clinically applicable approach to continuous prediction of future acute kidney injury. Nature, 572(7767), 116–119.

Wu, C. C., Yeh, W. C., Hsu, W. D., Islam, M. M., Nguyen, P. A. A., Poly, T. N., ... & Li, Y. C. J. (2019). Prediction of fatty liver disease using machine learning algorithms. Computer Methods and Programs in Biomedicine, 170, 23–29.

Younis, M. C. (2021). Evaluation of deep learning approaches for identification of different corona-virus species and time series prediction. Computerized Medical Imaging and Graphics, 90, 101921. https://doi.org/10.1016/j.compmedimag.2021.101921

Zhou, L. Q., Wang, J. Y., Yu, S. Y., Wu, G. G., Wei, Q., Deng, Y. B., ... & Dietrich, C. F. (2019). Artificial intelligence in medical imaging of the liver. World Journal of Gastroenterology, 25(6), 672–689.