ijecs open access www.ijecs.in
International Journal of Engineering and Computer Science
Volume 14 Issue 03 March 2025, Page No. 26964-26969
ISSN: 2319-7242 DOI: 10.18535/ijecs/v14i03.5044

Ultrasound Image-Based Liver Disease Diagnosis Using Machine Learning

Frank Edughom Ekpar [1*]

[1] Scholars University Ltd; Rivers State University; Topfaith University, Nigeria

Abstract

A dataset comprising liver B-mode ultrasound image sequences is processed to construct a system to automatically detect non-alcoholic fatty liver disease (NAFLD) - also called metabolic dysfunction-associated steatotic liver disease (MASLD) - via machine learning-based binary classification. Owing to the paucity of samples in the dataset, alternatives to the widely used convolutional neural network (CNN) and similar deep learning approaches are adopted since harnessing CNN and comparative systems is likely to result in overfitting of the data. Simpler alternative machine learning approaches such as random forest classifier, logistic regression and decision tree classifier are employed, compared and contrasted. For the minimal datasets utilized, these simpler approaches resulted in reasonable performance metrics. Further refinement of the techniques could permit improvements in robustness and performance that could warrant incorporation of the resulting machine learning models into modules for the automated detection of liver disease based on ultrasound image sequences in a comprehensive artificial intelligence-driven healthcare system.

Keywords: Machine Learning (ML), Artificial Intelligence (AI), Deep Learning (DL), Convolutional Neural Network (CNN), Random Forest Classifier, Logistic Regression, Decision Tree Classifier, Non-Alcoholic Fatty Liver Disease (NAFLD), Healthcare System, Disease Diagnosis and Prediction

1. Introduction

Non-alcoholic fatty liver disease (NAFLD), also called metabolic dysfunction-associated steatotic liver disease (MASLD), is the most common form of liver disease [1] in the world. Although it typically does not cause serious illness in many people affected by the condition, it can lead to more severe liver disease, namely, non-alcoholic steatohepatitis (NASH) in some cases.

NAFLD can be detected via the analysis of liver B-mode ultrasound image sequences. As with many other health conditions, early detection could lead to improved health outcomes. Related work has been reported on the automated detection, prediction and diagnosis of a wide range of diseases such as diabetes, chronic kidney disease, and so on, based on a wide range of systems, algorithms and techniques [2] – [20] with varying degrees of success and featuring a mix of merits and demerits. More recently, Ekpar [21] – [24] introduced a comprehensive artificial intelligence-driven healthcare system with a modular design to accommodate a wide range of health conditions for the automated detection, prediction, diagnosis and management of the incorporated health conditions and to provide timely and actionable insights for clinical decision support. One of the unique features of the system created by Ekpar [21] – [24] is support for novel three-dimensional multilayer electroencephalography (Ekpar EEG) systems that permit non-invasive simultaneous capture of distinct signal streams from multiple layers within the brain, enabling greater insights into brain-related health conditions, rehabilitation and practical human machine interfaces (HMIs) such as high-performance brain computer interfaces (BCIs) and brain-to-brain communication [25] –

[27]. By obviating the need for surgical implantation of electrodes in the brain while permitting the high performance currently only possible through expensive, risky and inconvenient implants, Ekpar EEG [25] – [27] represents a game-changer in EEG and the myriads of related applications ranging from medicine to computing.

In this paper, machine learning (ML) algorithms are employed to construct models for the automated detection of non-alcoholic fatty liver disease (NAFLD) via the processing of liver B-mode ultrasound images. The approaches adopted are informed by the small number of samples in the dataset and serve as alternatives to convolutional neural networks and other deep learning approaches that could lead to overfitting.

2. Materials and Methods

Participant Recruitment

People volunteered to take part in the research that helped develop the AI-driven healthcare system. All participants gave informed consent before engaging in the studies.

Ethical Approval

The Health Research Ethics Committee at Rivers State University Teaching Hospital, affiliated with Rivers State University, approved the ethical aspects of the research. The study followed all relevant ethical guidelines and regulations. Publicly accessible data were used in accordance with the licensing terms established by the original creators.

3. Methodology

Publicly accessible healthcare datasets can be enriched by integrating data from local experiments and data collection projects. This combined dataset can then be used to train AI models capable of making actionable predictions based on new data inputs. Examples of public healthcare dataset sources include the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

By incorporating local data, the model is strengthened, bias is reduced, and inclusivity and global applicability are ensured. A key aspect of this project is merging diagnostic data—such as electrocardiographic results—from local studies with EEG data, using both traditional and cutting-edge three-dimensional multilayer EEG systems. Ethical approval for local data collection has been granted by research ethics committees in the respective regions, and partnerships have been established with licensed medical doctors who have direct access to patients and healthcare professionals. These doctors are contributing anonymized clinical data to validate the AI models.

Once trained, the AI models will be integrated into a comprehensive healthcare system to assist medical professionals with clinical decision-making and support the development of Brain-Computer Interfaces (BCIs). This system will provide actionable predictions and insights based on new clinical data from healthcare providers, aiding in the early detection, diagnosis, treatment, prediction, and prevention of conditions such as diabetes, heart disease, stroke, autism, and epilepsy. This project is committed to advancing open science, reproducibility, and collaboration, with the resulting data being made available on public platforms like GitHub.

4. System Design and Implementation

The healthcare system described in this paper is built with a modular approach, where each health condition (such as liver disease, chronic kidney disease, diabetes, heart disease, stroke, epilepsy, autism, etc.) is handled by a distinct module. This setup allows for future expansion to include additional conditions, while also facilitating the efficient update of existing modules with new data. Modules designed for Brain-Computer Interfaces (BCIs), including those utilizing motor imagery, can process EEG data to generate actionable commands and appropriate responses.

The system also provides guidelines for adapting traditional EEG systems to cutting-edge three-dimensional multilayer EEG systems. These innovative systems, developed by Ekpar [25] – [27], follow a conceptual framework that uses approximations of key bio-signal features to analyze or influence the biological systems. For each module, advanced AI models are created and trained on properly formatted data, as detailed in the paper. These AI models can integrate genetic, environmental, lifestyle, and other relevant factors to offer more precise representations of the participants' situations.

Figure 1 shows key aspects of the system.

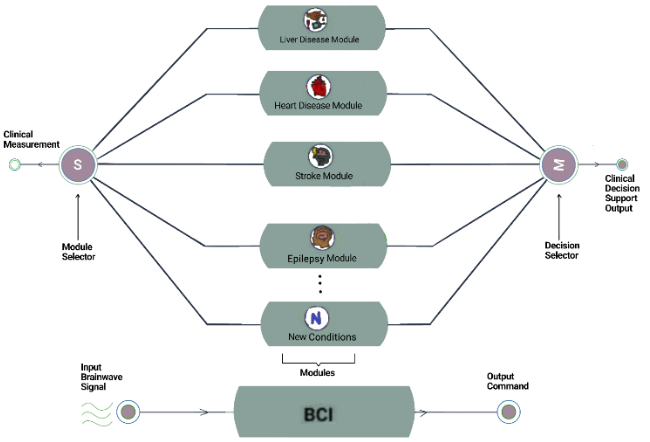

Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are created using four distinct approaches:

1. Direct Use of large language models (LLMs) like GPT-4 as inference engines, utilizing data in the form of multidimensional input vectors. This may include fine-tuning the LLM.
2. Prompt Engineering for LLMs such as Bard and GPT-4 (and future versions) to outline a series of actions for building the AI system. These steps are implemented using the creator's expertise in AI, neural networks, deep learning, Python, TensorFlow, Keras, and other machine learning and visualization tools like Scikit-learn and Matplotlib.
3. Automated AI Model Generation through LLMs like Bard and GPT-4 (and their future versions) via an automated pipeline to produce specific models.
4. Direct AI Architecture Design based on the creator's extensive knowledge of AI, neural networks, deep learning, Python, TensorFlow, Keras, and other ML and visualization tools such as Scikit-learn and Matplotlib.

All methods and tools used in developing the solution are thoroughly documented to ensure easy transfer and reuse of the system.

The AI models generated are assessed and compared based on their performance (using metrics like specificity, sensitivity, etc.) and their effectiveness in addressing the challenges under consideration.

Automated Non-Alcoholic Fatty Liver Disease (Nafld) Diagnosis Based on Liver B-Mode Ultrasound Images

The fourth approach is adopted and as outlined in the foregoing, involves the construction of custom AI models. Due to the paucity of images in the dataset utilized, alternatives were adopted to convolutional neural networks and similar deep learning approaches that could result in overfitting. Simpler machine learning models including Random Forest Classifier, Logistic Regression and Decision Tree Classifier were experimented with.

5. Dataset

A dataset containing liver B-mode ultrasound image sequences donated by Byra et al [28] was obtained from the publicly accessible Kaggle dataset repository. The dataset contained a total of 55 images out of which 17 images were in the class 0 (normal) while 38 images were in class 1 (fatty). Each image was 434 x 636 pixels.

Figure 2 illustrates a selection of images and their corresponding classes.

Data Availability

Liver B-mode liver ultrasound images were retrieved from the Kaggle dataset repository at https://www.kaggle.com/datasets/shanecandoit/dataset-of-bmode-fatty-liver-ultrasound-images

and harnessed for this study.

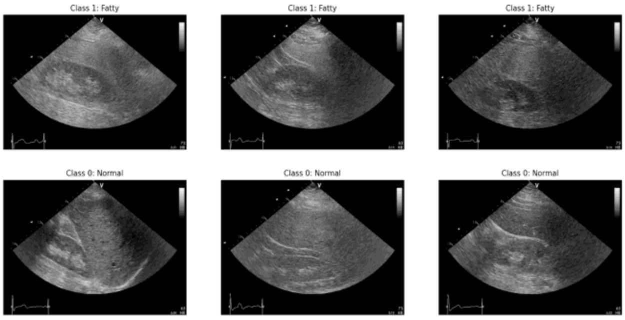

Fig. 2: Selection of images and their corresponding classes.

6. Results

As an alternative to convolutional neural networks and similar deep learning systems that could be constrained by overfitting as a consequence of the small number of samples in the dataset, experiments were carried out with three simpler machine learning approaches, namely, Random Forest Classifier, Logistic Regression and Decision Tree Classifier from the Scikit-learn toolkit.

The dataset was split into a training set with 80% of the original data and a testing/validation set with the remaining 20% of the data. Using a random state value of 42, Table 1, Table 2 and Table 3 summarize the performance metrics for Random Forest Classifier, Logistic Regression and Decision Tree Classifier, in that order.

Table 1: Performance Metrics for Random Forest Classifier

Class	Precision	Recall	F1-Score	Support
0	0.50	0.67	0.57	3
1	0.86	0.75	0.80	8
Accuracy			0.73	11
Macro Average	0.68	0.71	0.69	11
Weighted Average	0.76	0.73	0.74	11

Table 2: Performance Metrics for Logistic Regression

Class	Precision	Recall	F1-Score	Support
0	0.67	0.67	0.67	3
1	0.88	0.88	0.88	8
Accuracy			0.82	11
Macro Average	0.77	0.77	0.77	11
Weighted Average	0.82	0.82	0.82	11

Table 3: Performance Metrics for Decision Tree Classifier

Class	Precision	Recall	F1-Score	Support
0	0.50	0.67	0.57	3
1	0.86	0.75	0.80	8
Accuracy			0.73	11
Macro Average	0.68	0.71	0.69	11
Weighted Average	0.76	0.73	0.74	11

approach.

7. Conclusion

This paper presented a system for the automated detection of non-alcoholic fatty liver disease (NAFLD) - also called metabolic dysfunction-associated steatotic liver disease (MASLD) - based on B-mode ultrasound images. The paucity of the samples in the dataset utilized for training of the models necessitated the adoption of alternatives to convolutional neural network (CNN) and similar deep learning (DL) approaches to avoid overfitting of the data. Simpler machine learning systems like random forest classifier, logistic regression and decision tree classifier were tried and the performance metrics compared and contrasted. The availability of more data samples would enable the adoption of CNN, DL or similar approaches and with enhancements in performance and robustness, the possibility of incorporation as modules for automated NAFLD detection within the framework of a comprehensive artificial intelligence (AI)-powered healthcare system.

Conflicts of Interest

There are no conflicts of interest to disclose.

References

1. NHS – Non-alcoholic Fatty Liver Disease (NAFLD): https://www.nhs.uk/conditions/non-alcoholic-fatty-liver-disease. Retrieved (2025).
2. Nomura, A., Noguchi, M., Kometani, M., Furukawa, K., Yoneda, T. Artificial Intelligence in Current Diabetes Management and Prediction, Curr Diab Rep. 21(12):61 (2021).
3. Kumar, Y., Koul, A., Singla, R., Ijaz, M. F. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda, Journal of Ambient Intelligence and Humanized Computing 14:8459–8486 (2023).
4. Ansari, S., Shafi, I., Ansari, A., Ahmad, J., Shah, S. I. Diagnosis of liver disease induced by hepatitis virus using artificial neural network, IEEE Int Multitopic. https://doi.org/10.1109/INMIC.2011.6151515 (2011).
5. Battineni, G., Sagaro, G. G., Chinatalapudi, N., Amenta, F. Applications of machine learning predictive models in the chronic disease diagnosis, J Personal Med. https://doi.org/10.3390/jpm10020021 (2020).
6. Abdar, M., Yen, N., Hung, J. Improving the diagnosis of liver disease using multilayer perceptron neural network and boosted decision tree, J Med Biol Eng 38:953–965 (2018).
7. Chaikijurajai, T., Laffin, L., Tang, W. Artificial intelligence and hypertension: recent advances and future outlook, Am J Hypertens 33:967–974 (2020).
8. Fujita, S., Hagiwara, A., Otsuka, Y., Hori, M., Takei, N., Hwang, K. P., Irie, R., Andica, C., Kamagata, K., Akashi, T., Kumamaru, K. K., Suzuki, M., Wada, A., Abe, O., Aoki, S. Deep Learning Approach for Generating MRA Images From 3D Quantitative Synthetic MRI Without Additional Scans, Invest Radiol 55:249–256 (2020).
9. Juarez-Chambi, R. M., Kut, C., Rico-Jimenez, J. J., Chaichana, L. K., Xi, J., Campos-Delgado, D. U., Rodriguez, F. J., Quinones-Hinojosa, A., Li, X., Jo, J. A. AI-Assisted In Situ Detection of Human Glioma Infiltration Using a Novel Computational Method for Optical Coherence Tomography, Clin Cancer Res 25(21):6329–6338 (2019).
10. Nashif, S., Raihan, R., Islam, R., Imam, M. H. Heart Disease Detection by Using Machine Learning Algorithms and a Real-Time Cardiovascular Health Monitoring System, World Journal of Engineering and Technology Vol 6, No. 4 (2018).
11. Chen, P. H. C., Gadepalli, K., MacDonald, R., Liu, Kadowaki, S., Nagpal, K., Kohlberger, T., Dean, J., Corrado, G. S., Hipp, J. D., Mermel, C. H., Stumpe, M. C. An augmented reality microscope with real time artificial intelligence integration for cancer diagnosis, Nat Med 25:1453–1457 (2019).
12. Gouda, W., Yasin, R. COVID-19 disease: CT Pneumonia Analysis prototype by using artificial intelligence, predicting the disease severity, Egypt J Radiol Nucl Med 51(1):196 (2020).
13. Han, Y., Han, Z., Wu, J., Yu, Y., Gao, S., Hua, D., Yang, A. Artificial Intelligence Recommendation System of Cancer Rehabilitation Scheme Based on IoT Technology, IEEE Access 8:44924–44935 (2020).
14. Chui, C. S., Lee, N. P., Adeoye, J., Thomson, P., Choi, S. W. Machine learning and treatment outcome prediction for oral cancer, J Oral Pathol Med 49(10):977–985 (2020).
15. Koshimizu, H., Kojima, R., Okuno, Y. Future possibilities for artificial intelligence in the practical management of hypertension, Hypertens Res 43:1327–1337 (2020).

16. Kather, J. N., Pearson, A. T., Halama, N., Jäger, D., Krause, J., Loosen, S. H., Marx, A., Boor, P., Tacke, F., Neumann, U. P., Grabsch, H. I., Yoshikawa, T., Brenner, H., Chang-Claude, J., Hoffmeister, M., Trautwein, C., Luedde, T. Deep learning microsatellite instability directly from histology in gastrointestinal cancer, Nat Med 25:1054–1056 (2019).
17. Kwon, J. M., Jeon, K. H., Kim, H. M., Kim, M. J., Lim, S. M., Kim, K. H., Song, P. S., Park, J., Choi, R. K., Oh, B. H. Comparing the performance of artificial intelligence and conventional diagnosis criteria for detecting left ventricular hypertrophy using electrocardiography, EP Europace 22(3):412–419 (2020).
18. Khan, M. A. An IoT Framework for Heart Disease Prediction Based on MDCNN Classifier, IEEE Access 8:34717–34727 (2020).
19. Oikonomou, E. K., Williams, M. C., Kotanidis, C. P., Desai, M. Y., Marwan, M., Antonopoulos, A. S., Thomas, K. E., Thomas, S., Akoumianakis, I., Fan, L. M., Kesavan, S., Herdman, L., Alashi, A., Centeno, E. H., Lyasheva, M., Griffin, B. P., Flamm, S. D., Shirodaria, C. Sabharwal, N., Kelion, A., Dweck, M. R., Van Beek, E. J. R., Deanfield, J., Hopewell, J. C., Neubauer, S., Channon, K. M., Achenbach, S., Newby, D. E., Antoniades, C. A novel machine learning-derived radiotranscriptomic signature of perivascular fat improves cardiac risk prediction using coronary CT angiography, Eur Heart J 40(43):3529–3543 (2019).
20. Sabottke, C. F., Spieler, B. M. The Effect of Image Resolution on Deep Learning in Radiography, Radiology: Artificial Intelligence Vol. 2. No. 1, 2:e190015 (2020).
21. Ekpar, F. E. A Comprehensive Artificial Intelligence-Driven Healthcare System, European Journal of Electrical Engineering and Computer Science, 8(3), Article 617. (2024).
22. Ekpar, F. E. Diagnosis of Chronic Kidney Disease Within a Comprehensive Artificial Intelligence-Driven Healthcare System, International Journal of Advanced Research in Computer and Communication Engineering, 13(9). (2024).
23. Ekpar, F. E. Image-based Chronic Disease Diagnosis Using 2D Convolutional Neural Networks in the Context of a Comprehensive Artificial Intelligence-Driven Healthcare System, Molecular Sciences and Applications, 4(13). (2024).
24. Ekpar, F. E. Leveraging Generative Artificial Intelligence Recommendations for Image-based Chronic Kidney Disease Diagnosis, International Journal of Advanced Research in Computer and Communication Engineering, 14(1). (2025).
25. Ekpar, F. E. A Novel Three-dimensional Multilayer Electroencephalography Paradigm, Fortune Journal of Health Sciences, 7(3). (2024).
26. Ekpar, F. E. System for Nature-Inspired Signal Processing: Principles and Practice, European Journal of Electrical Engineering and Computer Science, 3(6), pp. 1-10, (2019).
27. Ekpar, F. E. Nature-inspired Signal Processing, United States Patent and Trademark Office, US Patent Application Number: 13/674,035 (Filed: November 11, 2012, Priority Date: December 24, 2011), Document ID: US 20140135642 A1: Published: (2014).
28. Byra, M., Styczynski, G., Szmigielski, C., Kalinowski, P., Michałowski, L., Paluszkiewicz, R., Ziarkiewicz-Wróblewska, B., Zieniewicz, K., Sobieraj, P., Nowicki, A. Transfer learning with deep convolutional neural network for liver steatosis assessment in ultrasound images, International Journal of Computer Assisted Radiology and Surgery, 13:1895-1903. (2018).