International Journal of Scientific Research in Computer Science, Engineering and Information Technology
ISSN : 2456-3307
OPEN ACCESS
Available Online at : www.ijsrcseit.com
doi : https://doi.org/10.32628/CSEIT25113395

Detection of Liver Cirrhosis using a Web-Based Convolutional Neural Network System

Adeoti Babajide E[1]*, Lawani Benjamin[1], Ayoola Oluwatorera[1], Mgbeahuruike Emmanuel[1], Adebanjo Samuel A[1], Oladunjoye Michael[2]

*[1]Department of Software Engineering, Babcock University, Ilishan-Remo, Ogun State, Nigeria
[2]Department of Computer Science, Federal University of Technology, Akure, Ondo-state Nigeria

ARTICLEINFO

Article History:

Accepted : 01 July 2025
Published: 04 August 2025

Publication Issue
Volume 11, Issue 4
July-August-2025

Page Number
316-321

ABSTRACT

Liver cirrhosis, a critical health condition marked by irreversible scarring of the liver, contributes significantly to global morbidity and mortality. Traditional diagnostic methods are invasive, costly, and often detect the disease at advanced stages. This study presents the design and implementation of a non-invasive, web-based liver cirrhosis detection system employing Convolutional Neural Networks (CNNs). The system aims to support early diagnosis and prognosis using medical imaging and machine learning. The implemented system demonstrates high accuracy in classifying cirrhotic conditions and offers a scalable solution for under-resourced medical facilities

Keywords: Liver Cirrhosis, Convolutional Neural Network, Deep Learning, Medical Image Classification, Web-Based System, Early Diagnosis.

Introduction

Liver cirrhosis is the terminal phase of chronic liver disease, leading to compromised liver function and increased risk of liver failure. Its early detection is crucial but challenging, particularly in low-resource settings where medical instrumentation is limited. Traditional diagnostics, such as liver biopsy and imaging techniques like CT, MRI, and ultrasound, although effective, are expensive and inaccessible to many.[1]

Machine learning has emerged as a promising tool for the detection and classification of liver cirrhosis, a condition characterized by progressive liver scarring. Various machine learning models have been developed to aid in the early diagnosis and management of this disease, leveraging clinical and laboratory data to predict cirrhosis stages and identify individuals at risk. These models utilize a range of algorithms, including both ensemble and non-ensemble methods, to enhance prediction accuracy and facilitate early intervention. The diagnosis of early-stage liver cirrhosis using conventional methods presents a risk of misdiagnosis in patients who do not present normal symptoms which in turn worsens the risk of liver disease and ultimately liver failure. Therefore, the creation of a detection system is imperative. Research from The National Library of Medicine and Science Direct underscores the growing global impact of liver diseases. Currently the 11th leading cause of death worldwide, liver diseases, particularly cirrhosis, continue to rise [4]. In Africa, liver diseases rank as the 10th leading cause of death due to factors like chronic alcohol consumption and hepatitis B and C [10][16]. Liver cirrhosis alone claims over two million lives annually, with a significant increase observed since 1990 [11]. To address this issue, this study aims to develop a liver cirrhosis detection web-based system for medical institutions lacking adequate medical instrumentation, serving areas with a high prevalence of undiagnosed individuals at risk.

The aim of this project is to design and implement a web-based liver cirrhosis detection system using Convolutional Neural Network (CNN) model.

The specific objectives of these research are to:

i. Implement a machine learning(CNN model) based detection system to identify liver cirrhosis
ii. Develop a liver disease classification model
iii. Implement prognosis predictions using identifiable qualities
iv. Implement of a simple, explanatory user interface to explain the results of the predictions.

To address this, we propose a web-based liver cirrhosis detection system powered by CNNs. The system processes medical images to detect early signs of cirrhosis, providing rapid and accurate diagnostics through a user-friendly interface, and is deployable across devices with a web browser

Another researcher presents a machine learning-based framework for the prediction and classification of liver cirrhosis using routinely available laboratory test data [12]. The study addresses the clinical challenge of early cirrhosis detection without relying on invasive procedures like biopsies. Instead, it leverages widely accessible metrics such as SGPT, SGOT, ALB, bilirubin levels, and platelet count to stratify patients into three cirrhosis stages: F0–F1 (normal), F2 (moderate fibrosis) whileF3–F4 (severe/complete cirrhosis)

[12] applies and compares several machine learning classifiers such as support Vector Machines (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Naïve Bayes, and Gradient Boosting on a dataset of 730 Egyptian liver patients.

Gradient Boosting outperformed all other models with an accuracy of 86% (training) and 100% (testing). Artificial Neural Networks achieved 83.4% training accuracy and 99.2% testing accuracy.

Naïve Bayes and SVM yielded lower testing accuracies at 53.6% and 89.6% respectively.

[7] Investigate the application of deep learning the goal of this research is to Improve cirrhosis detection accuracy through deep learning and feature engineering specifically using Convolutional Neural Networks (CNNs) for non-invasive detection of liver cirrhosis using a publicly available clinical dataset. This dataset comprises 418 patient records with 20 clinical features sourced from Kaggle. The study benchmarks CNN performance against traditional machine learning models, including Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbors (KNN), Gaussian Naïve Bayes (GNB), and Gradient Boosting (GBoost)

[7] built a custom CNN architecture which was developed and trained. Its performance was compared to baseline ML classifiers using standard evaluation metrics such as accuracy, precision, recall, and F1-score.

Result of this investigation shows that CNN model outperformed all baseline models, achieving 84% accuracy, with strong precision, recall, and F1 metrics. However Traditional models performed notably lower, underscoring the CNN's ability to automatically detect complex, non-linear feature interactions.[7]

[3] present a machine learning–based predictive system aimed at detecting liver cirrhosis early using clinical data. The work was presented at the 8th International Conference on Computing, Communication, Control and Automation (ICCUBEA)

and represents a continued effort in transitioning from invasive diagnostic methods to data-driven, non-invasive prediction models.

[3] Utilizes a clinical dataset of liver disease cases, sourced from standard hospital records, as part of data pre-processing methods, the harvested clinical dataset was cleaned, normalized, and the missing values where handled appropriately, ensuring high-quality input for model training, the researchers explored several machine learning classifiers which includes Support Vector Machines (SVM), Decision Trees, and Random Forests, with the random Forest emerging as the highest-performing model among the tested algorithms, whose accuracy is 97% accuracy, confirming its robustness in medical prediction tasks

METHODS AND MATERIAL

A. Data Acquisition and Preprocessing

The dataset used to train the liver cirrhosis detection model was gotten from an open-source website for computer vision datasets called Roboflow. This dataset was published by Abhishek Dada. The dataset comprised of 3976 images total; 2776 images in the training dataset and 1200 images in validation dataset. There were no augmentations performed in the dataset originally.

The dataset used to train the random forest classifier was created to predict the survival state of patients with liver cirrhosis, focusing on 17 clinical features. These features help classify patients into three survival states: death, censored, or censored due to liver transplantation. The data originates from a Mayo Clinic study conducted from 1974 to 1984 on primary biliary cirrhosis (PBC), a condition resulting from prolonged liver damage. The dataset represents individuals who participated in a randomized placebo-controlled trial testing the drug D-penicillamine, as well as those who did not join the trial but agreed to record basic metrics and undergo survival tracking. The dataset was funded by the Mayo Clinic. Data augmentations included dropping rows with missing values in the drug column, imputing missing values with the mean, and one-hot encoding categorical attributeson primary biliary cirrhosis (PBC), a condition resulting from prolonged liver damage.

B. System Architecture

A CNN model architecture was constructed using layers of deep convolutional Network, pooling, dropout, and dense operations. The architecture was optimized for high classification accuracy and efficient computation. Training used standard back propagation with categorical cross-entropy loss and Adam optimizer.

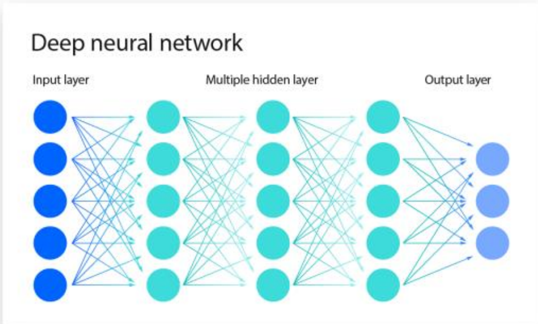

Figure 1: Deep Neural Network Architecture.

Server-Side Architecture.

The server-side architecture is responsible for data processing, model inference, and handling client requests. Python, is utilized for backend development. PyTorch, a deep learning framework, is integrated into the server-side logic to deploy the convolutional neural network (CNN) model for liver cirrhosis detection. This model is trained using PyTorch, leveraging its flexibility and efficiency in building machine learning models.

Communication Protocols:

Communication between the client and server components is facilitated through HTTP(S) protocols, ensuring secure transmission of medical imaging data.

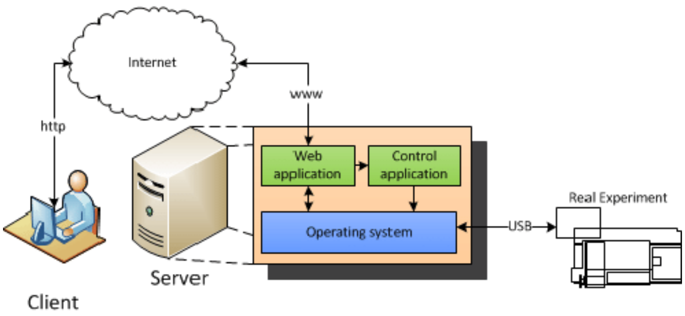

Figure 2: Client-Server Architecture

C. Web Deployment.

The model was deployed using the Streamlit library in Python, enabling real-time interaction via a browser. The system provides options for image upload, prediction output, prognosis estimation, and explanatory visualization.

RESULTS AND DISCUSSION

Result

The web-based liver cirrhosis detection system has a significant impact on diagnostics, particularly in the field of liver disease. The system makes us of technologies such as Python, PyTorch, and Streamlit, the system offers several key benefits that enhance the diagnostic process. Some of the benefits includes

The system provides a fast and efficient means of diagnosing cirrhosis disease. With the ability to analyze images in real-time, medical professionals can quickly assess whether a patient's liver is indicative of cirrhosis, allowing for prompt treatment and management.

Secondly, the system improves the accuracy of diagnoses. The PyTorch model used in the system is trained on a large dataset of liver images, enabling it to recognize patterns and features indicative of cirrhosis with accuracy of around 84 percent. This reduces the likelihood of misdiagnosis and ensures that patients receive the appropriate care.

Additionally, the system enhances the accessibility of diagnostic tools. By providing user-friendly interface, the system can be easily used by medical professionals with varying levels of expertise. This helps to democratize access to advanced diagnostic technologies, particularly in regions where access to healthcare resources may be limited.

Overall, the web-based liver cirrhosis detection system has a transformative impact on diagnostics, offering a fast, accurate, and accessible tool for the diagnosis and classification of cirrhosis disease.

Discussion.

The trained CNN model achieved high accuracy and recall on test datasets, indicating robust performance in classifying cirrhotic versus non-cirrhotic cases. AUC values exceeded 0.90, showing the model's reliability. Prognosis prediction further enriched the decision support capabilities.

The system demonstrated usability across devices, ensuring accessibility in rural or under-resourced settings. Compared to traditional methods, it reduces diagnostic delay and supports early intervention.

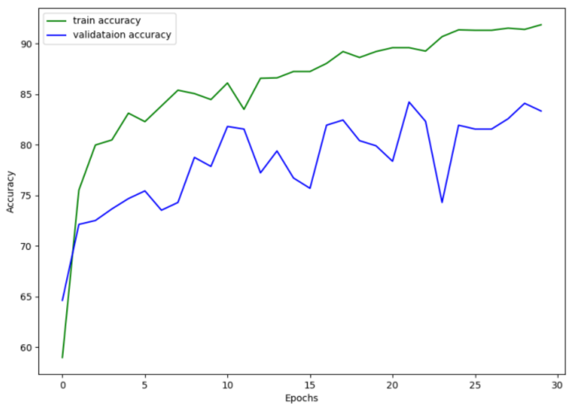

Figure 3. A Convolutional Neural Network Classifier's Training and Validation Accuracy

CONCLUSION

In conclusion, the web-based liver cirrhosis detection system represents a significant advancement in medical technology. By integrating machine learning algorithms and web technologies, the system provides a valuable tool for medical professionals to improve the accuracy and efficiency of liver cirrhosis diagnosis. The system's user-friendly interface and automated analysis process make it a valuable asset in the field of liver disease diagnosis.

References

[1]. Al-Hasani, M., Sultan, L. R., Sagreiya, H., Cary, T. W., Karmacharya, M. B., & Sehgal, C. M. (2022). Machine learning improves early detection of liver fibrosis by quantitative ultrasound radiomics. IEEE International Ultrasonics Symposium, 2022

[2]. Amin, R., Yasmin, R., Ruhi, S., Rahman, M. H., & Reza, M. S. (2023). Prediction of chronic liver disease patients using integrated projection based statistical feature extraction with machine learning algorithms. Informatics in Medicine Unlocked, 36, 101155.

[3]. Bhute, P., Gahane, S., Kapse, A., Mohadure, S., Raut, E., & Khode, P. (2024, December). Cloud Cryptography in IT Infrastructure: A Comprehensive Review and Future Directions. In 2024 International Conference on Sustainable Communication Networks and Application (ICSCNA) (pp. 528-533). IEEE.

[4]. Blesl, A., & Stadlbauer, V. (2021). The gut-liver axis in cholestatic liver diseases. In Nutrients (Vol. 13, Issue 3, pp. 1–32). https://doi.org/10.3390/nu13031018

[5]. Devarbhavi, H., Asrani, S. K., Arab, J. P., Nartey, Y. A., Pose, E., & Kamath, P. S. (2023). Global burden of liver disease: 2023 update. Journal of Hepatology, 79(2), 516–537. https://doi.org/10.1016/j.jhep.2023.03.017

[6]. Ehman, R. L. (2022). Magnetic resonance elastography: from invention to standard of care. Abdominal Radiology, 47(9), 3028–3036. https://doi.org/10.1007/s00261-022-03597-z

[7]. Endah, M., Wijaya, R. N., Ahsan, H. K., & Endah Hiswati, M. (2023). Enhancing cirrhosis detection: A deep learning approach with convolutional neural networks. Journal of Soft Computing Exploration. https://doi.org/10.52465/joscex.v4i4.226

[8]. Hamid, K., Asif, A., Abbasi, W., & Sabih, D. (2017). Machine learning with abstention for automated liver disease diagnosis. 2017 International Conference on Frontiers of Information Technology (FIT), 356–361.

[9]. Ignat, S.-R., Dinescu, S., Hermenean, A., & Costache, M. (2020). Cellular interplay as a consequence of inflammatory signals leading to liver fibrosis development. Cells, 9(2), 461.

[10]. Kaiser, S., Sziranyi, J., & Groß, D. (2020). The hepatopathologist Hans Popper (1903–1988). Der Pathologe, 41(1), 30–38. https://doi.org/10.1007/s00292-019-0619-y

[11]. Liu, Z.-P., Ouyang, G.-Q., Huang, G.-Z., Wei, J., Dai, L., He, S.-Q., & Yuan, G.-D. (2023). Global burden of cirrhosis and other chronic liver diseases due to nonalcoholic fatty liver disease, 1990-2019. World Journal of Hepatology, 15(11), 1210–1225. https://doi.org/10.4254/wjh.v15.i11.1210

[12]. Mazen, T. Sh. (2023). Machine Learning-based Segmentation to the Prediction of Liver Cirrhosis. International Journal of Computer Applications, 185(23), 13–20. https://doi.org/10.5120/ijca2023922973

[13]. Meza, J. K. S., Yepes, D. O., Rodrigo-Ilarri, J., & Cassiraga, E. (2019). Predictive analysis of urban waste generation for the city of Bogotá, Colombia, through the implementation of decision trees-based machine learning, support vector machines and artificial neural networks. Heliyon, 5(11).

[14]. Mousa, O. Y., & Kamath, P. S. (2021a). A History of the Assessment of Liver Performance. In Clinical Liver Disease (Vol. 18, Issue S1, pp. 28–48). https://doi.org/10.1002/cld.1100

[15]. Mousa, O. Y., & Kamath, P. S. (2021b). An Official Learning Resource of AASLD review a History of the assessment of liver Performance. 28 | CliniCal Liver Disease, 18, 1. https://doi.org/10.1002/cld.1100/suppinfo

[16]. Ndow, Gibril, Erwan Vo-Quang, Yusuke Shimakawa, Amie Ceesay, Saydiba Tamba, Harr F. Njai, Lamin Bojang et al. "Clinical characteristics and outcomes of patients with cirrhosis and hepatocellular carcinoma in The Gambia, west Africa: a prospective cohort study." The Lancet Global Health 11, no. 9 (2023): e1383-e1392.

[17]. Prakash, B., Vennela, D., Lakshmi, D., & Priyanka, S. S. (2024). Stage Prediction of Liver Cirrhosis Disease using Machine Learning. 1–6. https://doi.org/10.1109/icecsp61809.2024.10698096

[18]. Raschka, S., Patterson, J., & Nolet, C. (2020). Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. Information, 11(4), 193.

[19]. Singh, A., & Kaur, P. J. (2019). Analysis of Software Development Life Cycle Models BT - Proceeding of the Second International Conference on Microelectronics, Computing & Communication Systems (MCCS 2017) (V. Nath & J. K. Mandal (Eds.); pp. 689–699). Springer Singapore

[20]. Smith, D. R. (2022). Mechanical evaluation of structure and function in fibrous soft tissue using MR elastography. University of Delaware.

[21]. Wieczorek, M., Weston, A., Ledenko, M., Thomas, J. N., Carter, R., & Patel, T. (2022). A deep learning approach for detecting liver cirrhosis from volatolomic analysis of exhaled breath. Frontiers in Medicine, 9, 992703.

[22]. Wong, A., Anantrasirichai, N., Chalidabhongse, T. H., Palasuwan, D., Palasuwan, A., & Bull, D. (2021). Analysis of vision-based abnormal red blood cell classification. ArXiv Preprint ArXiv:2106.00389.

[23]. Yoo, J. J., Namdar, K., McIntosh, C., Khalvati, F., & Rogalla, P. (2022). A Comprehensive Study of Radiomics-based Machine Learning for Fibrosis Detection. ArXiv Preprint ArXiv:2211.14396.

[24]. Yoo, J. J., Namdar, K., McIntosh, C., Khalvati, F., & Rogalla, P. (2022). A Comprehensive Study of Radiomics-based Machine Learning for Fibrosis Detection. ArXiv Preprint ArXiv:2211.14396.