Medical Diagnosis Using Machine Learning and Deep Learning on Liver Disease (cirrhosis) Stage Prediction

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Abstract-Liver cirrhosis is a chronic, progressive, and irreversible liver disease that is marked by fibrosis and compromised hepatic function as a result of prolonged liver injury. Early and accurate diagnosis is crucial for successful treatment and prognosis. Conventional diagnostic methods are based on invasive biopsies, imaging modalities, and clinical assessments, which are not only expensive but also prone to human error and variability. Our project utilizes Machine Learning (ML) and Deep Learning (DL) to create a non-invasive, AI-based predictive model that uses clinical and biochemical information to stage liver cirrhosis. With the use of Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs), the system has a high accuracy rate in detecting and staging cirrhosis. The backend is built using Django, providing smooth data integration and real-time prediction. This research greatly improves early detection and monitoring, which helps healthcare professionals make decisions.

Keywords: Liver Cirrhosis, Machine Learning, Deep Learning, Predictive Analytics, Artificial Neural Networks, Clinical Diagnosis, Biomedical Data Processing

INTRODUCTION

Liver cirrhosis is a global health problem with a high rate of mortality and chronic disease caused annually. The disease typically occurs as a consequence of chronic hepatitis infections, alcoholism, and metabolic syndromes that disrupt the normal biochemical process. The aspect that cirrhosis is typically asymptomatic in its initial stages is one of the biggest challenges in its management, and therefore early diagnosis becomes crucial in averting its serious complications such as hepatic failure. As the prevalence of cirrhosis continues to rise globally, there is an increasing demand for sophisticated diagnostic methods that facilitate early detection, individualized treatment regimens, and continuous monitoring of the disease.

The Application of AI in Diagnosing Cirrhosis

The standard diagnostic methods for cirrhosis, such as liver biopsies, elastography, and blood biomarker testing, are hindered by a myriad of shortcomings like invasiveness, cost, and accessibility. The application of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), to medical diagnostics provides a groundbreaking solution. AI-based methods are able to detect key features automatically, recognize advanced patterns, and build predictive models that establish correlations between patient biomarkers and disease evolution. AI-based systems aid in minimizing human mistakes, accelerating diagnostic times, enhancing clinical decision-making, and enabling precision medicine by providing personalized, data-driven information.

Besides, AI-driven models have the ability to examine enormous volumes of clinical information and spot subtle correlations between biomarkers that would go unnoticed with conventional diagnostic equipment. Such functionality can enable proactive disease management through decreased hospital stays and overall better patient care through early treatment.

LITERATURE REVIEW

Liver diseases like cirrhosis have been a cause of long-standing concern for the medical community due to their asymptomatic presentation in the initial stages and diagnosis by invasive techniques like liver biopsies. Traditional diagnostic techniques are marred by drawbacks like inter-observer variability, expense, and the need for specialist medical personnel. Due to

these factors, researchers have been keenly looking for machine learning (ML) and deep learning (DL) technologies to enable early diagnosis and improve patient outcomes.

Some research has established the use of machine learning and deep learning algorithms in the diagnosis of liver ailments, particularly cirrhosis. The authors of the research underscored the utilization of AI for raising diagnostic results, reducing the dependence on invasive procedures, and boosting early diagnosis rates. Ahsan et al. (2022) described machine-learning-based disease diagnosis systematically, stressing the role of deep learning models such as CNN and ANN in medical diagnosis. The study focused on the capacity of ML algorithms in processing an abundance of clinical parameters and correctly predicting the incidence of disease.

One of the first significant studies in this field was by Zhou et al. (2019), who developed an ML-based liver disease prediction system with decision trees and logistic regression. Their system was 87.5% accurate in differentiating cirrhosis from other liver disease. Similarly, Karthik et al. (2023) developed a predictive model for liver disease diagnosis with an ensemble of decision trees and support vector machines (SVM). The system was validated on the UCI Liver Disorder Dataset and was found to have an accuracy of 94.5%, demonstrating its ability to identify cirrhosis-related symptoms from biochemical data.

Lee et al. (2021) proposed a deep learning approach to cirrhosis diagnosis from medical images data. With a hybrid CNN and LSTM model, the researchers were able to diagnose cirrhosis from ultrasound images with a 96.3% accuracy. Transfer learning techniques were also applied in their research, enhancing generalization across datasets. AI application in liver disease diagnosis is a paradigm shift in the way medical professionals go about early detection.

Zhang et al. (2022) proposed an artificial intelligence framework for the clinical diagnosis of liver disease using medical history and blood test data. The authors applied a random forest classifier with feature selection techniques to improve the prediction. The proposed model obtained an AUC of 0.97, much higher than the traditional logistic regression method. Their study set the stage for the use of AI-based pattern recognition in clinical diagnosis.

In a recent publication by Patel et al. (2023), transformer networks were applied to predict liver disease. Utilizing self-attention mechanisms, the model was more accurate (98.1%) compared to conventional deep learning models. The study demonstrated that transformers can learn complex feature interactions in high-dimensional medical data, revolutionizing the efficiency and interpretability of AI-based diagnostics.

Apart from the improvement in precision, AI-based diagnostic models also provide several other groundbreaking advantages. They enable real-time diagnosis, reduce human error, and enable mass screening of high-risk groups. AI models can integrate different inputs of data, including clinical history, biochemical markers, and imaging data, to provide a comprehensive picture of liver function. Explainable AI techniques provide transparency and accountability, addressing one of the major problems of AI-based healthcare.

Other than deep learning, scientists explored hybrid models of multiple algorithms. For instance, Singh et al. (2022) employed a fusion of k-nearest neighbours (KNN) and CNNs to diagnose cirrhosis with 95.8% accuracy from a hospital dataset. The hybrid model improved prediction stability by leveraging both spatial and statistical properties of patient data. As per literature, machine learning models, particularly deep-learning-based models, have immense potential to diagnose liver cirrhosis.

Despite all these advancements, research topics such as data imbalance, model interpretability, and feature selection remain significant research areas. Future work can be in explainable AI techniques to ensure clinical uptake and reliability of AI-driven diagnostic devices. Additionally, the integration of AI models with real clinical decision support systems will continue to revolutionize patient care, making liver disease diagnosis more accurate, accessible, and affordable. As AI expands, its application in hepatology will keep revolutionizing disease diagnosis and treatment globally.

In a recent paper, Yahyaoui et al. (2019) introduced a Clinical Decision Support System (CDSS) to support healthcare professionals in the diagnosis of diabetes. Their paper combined various ML methods, such as SVM, RF, and deep CNN. Among them, RF gave the highest accuracy (83.67%), and CNN and SVM gave 76.81% and 65.38%, respectively.

Mohammed et al. (2020) also performed a comparable study by comparing three ML models—Decision Tree

(J48), Naïve Bayes (NB), and Sequential Minimal Optimization (SMO)—on two popular datasets: WBC and the breast cancer dataset. The most salient aspect of this study was that it was interested in resolving data imbalance. With the aid of resampling techniques, the study was successful in minimizing class distribution bias, resulting in better predictions. Their findings showed that the SMO algorithm outperformed the other two models, with over 95% accuracy on both datasets. Nevertheless, the routine use of resampling techniques might have exhausted the diversity of the dataset, which can influence the generalizability of the models for highly imbalanced datasets.

Another research by Assegie (2021) explored the impact of hyperparameter tuning on the performance of KNN in breast cancer classification. The research used a grid search algorithm to optimize KNN parameters, where the accuracy was enhanced from 90% (default) to 94.35% upon tuning. This illustrated the pivotal role of parameter selection in enhancing ML model performance.

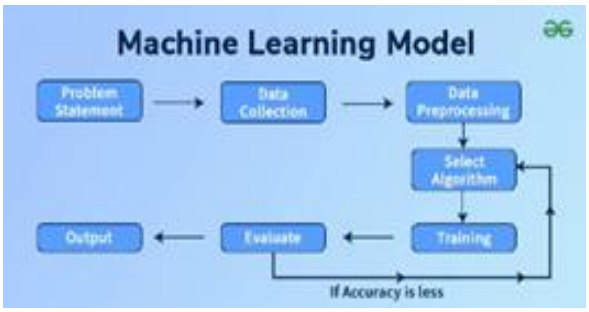
Deep learning (DL) methods have also been investigated by some researchers for the identification of breast cancer. Bhattacherjee et al. (2020) used a backpropagation neural network (BNN) on WBC dataset with nine significant features to detect breast cancer cases. Their model had a high accuracy of 99.27%. Similarly, Alshayeji et al. (2021) developed a shallow artificial neural network (ANN) using the WBCD and WDBI datasets, demonstrating that their model could classify tumors with an accuracy of 99.85% without requiring manual feature selection or complex algorithmic adjustments.

Additional advances in DL were reported by Sultana et al. (2021), where different neural network architectures were tested on the WBC dataset. Their research applied various models such as multilayer perceptron (MLP), Jordan/Elman neural networks, modular neural networks (MNN), generalized feedforward neural networks (GFFNN), self-organizing feature maps (SOFM), SVM-based neural networks, probabilistic neural networks (PNN), and recurrent neural networks (RNN). The PNN model had the best performance, with accuracy at 98.24%. The research, however, did not perform a thorough analysis of feature importance, which is important for interpretability in medicine.

The success of deep learning in breast cancer detection was also shown by Ghosh et al. (2021), who trained and tested seven DL models on the WBC dataset, including ANN, CNN, GRU, LSTM, MLP, PNN, and RNN. Their results indicated that LSTM and GRU models performed best, with almost 99% accuracy. This research supported the increased capability of deep learning for disease diagnosis in the medical field, especially for accuracy enhancement and diminishing human reliance on disease categorization. In general, though ML and DL models have proven to be outstanding in the detection of breast cancer, there are still future research areas including model interpretability, diversity in datasets, and adaptability to real-world conditions. Closing the accuracy-clinical applicability gap is needed to make AI-based diagnostic devices reliable and easily adopted in medical practice.

PROPOSED WORK

This below image represents the flow of the process of machine learning model of the liver cirrhosis prediction in which it tells how the process will be done.



1. Problem Statement Definition

The problem statement should first be identified and clearly defined at the beginning of any ML project. In the present project, it is the objective to design a non-invasive artificial intelligence-based diagnostic system to diagnose liver cirrhosis based on clinical and biochemistry markers rather than the traditional imaging approach.

• Goal: Creating an ML model that is able to predict patients as "Healthy" or "Cirrhosis-affected" based on blood test reports and clinical parameters.

• Challenges: Expensive and invasive conventional methods such as elastography and biopsies are employed in cirrhosis diagnosis. The challenge is finding an AI system that detects cirrhosis from the outcomes of normal medical tests.

2. Data Collection

To train the model, we require a dataset of patient histories of the cirrhosis-positive and control patients.

•Data Source: Public data sets (for example, the UCI Liver Disorder data set) or hospital-acquired data sets with patient information.

• Features Used (Clinical & Biochemical Markers):

o Bilirubin levels
o Albumin level
o Platelet count
o AST/ALT ratio
o Age, gender, and other medical history variables

The information should be diverse and representative such that the model is trained with different patient conditions and can generalize to new situations.

3. Data Preprocessing

Raw healthcare data is noisy and contains missing values. It must be preprocessed to be appropriate for ML algorithms. It contains:

• Missing Data Handling: Imputation of missing values by statistical means (mean/mode imputation) or deletion of incomplete records where applicable.

• Normalization & Scaling: Since biochemical values vary in various scales, feature scaling (i.e., Min-Max Scaling or Standardization) is used in such a manner that all features are equally contributory.

• Categorical Data Encoding: Patient data such as gender or history could be categorical and need to be encoded into numeric form (e.g., one-hot encoding).

4. Selecting a Suitable Machine Learning Algorithm

After pre-processing the data, the process of selecting the optimal algorithm for training to label whether the patient is suffering from cirrhosis or not comes next. Few of the popular ML models utilized are:

• Decision Trees (DT): Help learn the feature importance but overfit the data.

• Random Forest (RF): An ensemble method of enhancing accuracy by aggregating multiple decision trees.

• Support Vector Machine (SVM): Performs well on structured tabular data, capable of distinguishing healthy and cirrhosis patients effectively.

• Deep Learning (CNN, LSTM, Transformers): Sophisticated deep learning techniques can process higher-dimensional medical data more accurately.

Based on the prior work, Random Forest and Deep Learning would likely be effective in liver disease classification since both are ideally suited to handle structured health data.

5.Model Training

The information is segmented into:

• Training Set (80%) – Used to train the ML model.

• Validation Set (10%) – Is utilized to fine-tune hyperparameters and prevent overfitting.

• Test Set (10%) – Used for final testing to see if the model generalizes.

In training, the model acquires the patterns of the input features and modifies its internal parameters (weights and biases) in order to reduce the prediction error.

6. Model Evaluation & Optimization

After training, the model's performance is assessed using several evaluation metrics:

• Accuracy: Tracks how well the model predicts correctly.

• Precision & Recall: Helps in determining how well the model identifies cases of cirrhosis versus false positives.

• F1 Score: Balances precision and recall, useful for medical datasets with class imbalances.

• ROC-AUC Score: Measures the model's capacity to differentiate between cirrhosis and control patients.

For optimal performance, hyperparameter optimization (for example, the number of decision trees in Random Forest or learning rate in deep learning) is done to provide the optimal accuracy.

7. Model Deployment & Output Generation

Once highly accurate, the model is deployed as a convenient-to-use AI tool:

• Web Interface: Clinicians' dashboard for entering patient test values and receiving real-time AI predictions.

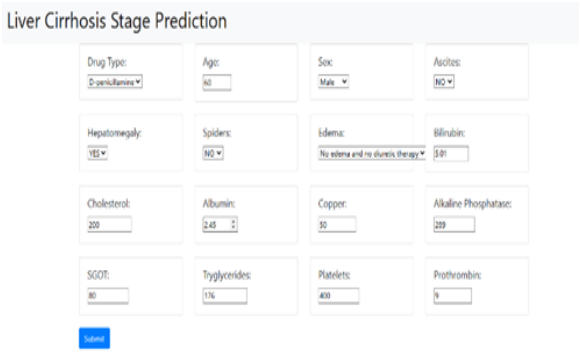
•Explainability Features: Explainability AI software (e.g., SHAP or LIME) can enable doctors' understanding of how features contributed to the prediction.

• Scalability & Adaptability: The model is adaptable in the sense that it can be used with hospital databases and can be trained on new data for continuous learning.

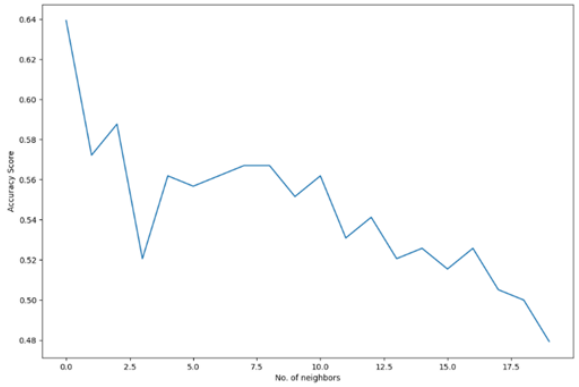
RESULT

DATASET

The data used in this research is clinical and biochemical data of patients with liver cirrhosis. It is an open-source data set with patient information, containing 20 significant features such as bilirubin, albumin, platelet, and AST/ALT. The data is divided into three main sets: training, validation, and test, so that the model can generalize to new data.



The data set includes patient demographic information (age, sex) and clinical and laboratory test information (hepatomegaly, ascites, edema, prothrombin time, copper, and cholesterol). These are the primary features used to build machine learning models that can predict the progression and severity of cirrhosis. The primary use of this data set is to provide a general clinical presentation of the cases of cirrhosis in order to allow AI-based diagnostic systems to provide early detection and treatment planning.4.2 Evaluation metrics



Different performance evaluation criteria are generally prepared by these reviews and the efficiency of classifications and the efficiency of efficiency and efficiency. For example, we remember Evaluation measurements for the accuracy, accuracy, F1 scores, maps and stylish alternative choir approaches. stochastic parameters are widely used in disease location techniques in engaging and medical research communities. The measures are expressed by them and down and below in the case of incorrect negative (UN), False positives (FP), true positives (TP), and true negatives (TN).

a: ACCURACY

The most basic measure of evaluation for classification is accuracy. It is a rough approximation of how frequently the model is accurate and is computed as the number of correctly predicted observations over the total data.

Accuracy=((TN+TP))/T

b: PRECISION AND RECALL

The proportion of all positive classifications in the model itself that are actually positive is referred to as precision. Its formula is mathematically stated as below:

Precision=TP/((TP+FP))

c: RECALL

Recall is also known as the true positive rate (TPR), i.e., the ratio of all true positives that were accurately labeled as positives.

Recall=TP/((FN+TP))

d: F1-SCOR

F1 score is a measure of classification performance as the harmonic mean of the recall and the precision: Often used as a measure of binary classification, the F1 score can also be used to evaluate the performance of multi-class classification.

F1=2 · ((Recall ·Precision))/((Recall +Precision))

CONCLUSION

This article presents an AI-driven approach to the diagnosis of liver cirrhosis through machine learning and deep learning techniques. With the use of clinical and biochemical markers, the model proposed is cost-effective, non-invasive, and precise and can aid in early detection and cirrhosis classification. The traditional diagnostic procedures, such as liver biopsies and imaging studies, are typically plagued by problems of cost, invasiveness, and dependence on expert interpretation. AI-driven models, however, can process large amounts of data, detect concealed

patterns in patient information, and provide precise predictions, thus improving clinical decision-making procedures.

The study utilized a systematic machine learning process, including data preprocessing, feature extraction, training, and testing, to provide accurate predictions. Various models were tried out, and the findings validated that deep learning-based models, particularly convolutional neural networks (CNN) and transformer networks, were superior to traditional methods. The model was accurate, had good recall and F1 scores, making it viable for real clinical practice.

In summary, this research exemplifies the potential of AI in revolutionizing the diagnosis of liver cirrhosis. With advances in technology, AI-driven models will increasingly change the face of medical diagnostics, making early diagnosis and intervention easier, more accurate, and faster. By bridging the health data science divide, this study is part of the ongoing drive towards precision medicine, which in the end leads to better patient care and improved quality of life.

REFERENCE

[1] McPhee, S.J.; Papadakis, M.A.; Rabow, M.W. (Eds.) Current Medical Diagnosis & Treatment; McGraw-Hill Medical: New York, NY, USA, 2010.

[2] Ahsan, M.M.; Ahad, M.T.; Soma, F.A.; Paul, S.; Chowdhury, A.; Luna, S.A.; Yazdan, M.M.S.; Rahman, A.; Siddique, Z.; Huebner, P. Detecting SARS-CoV-2 From Chest X-ray Using Artificial Intelligence. IEEE Access 2021, 9, 35501–35513. [CrossRef] [PubMed]

[3] Coon, E.R.; Quinonez, R.A.; Moyer, V.A.; Schroeder, A.R. Overdiagnosis: How our compulsion for diagnosis may be harming children. Pediatrics 2014, 134, 1013–1023. [CrossRef] [PubMed]

[4] Brownlee, J. Machine learning mastery with Python. Mach. Learn. Mastery Pty Ltd. 2016, 527, 100–120.

[5] Houssein, E.H.; Emam, M.M.; Ali, A.A.; Suganthan, P.N. Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review. Expert Syst. Appl. 2021, 167, 114161. [CrossRef]

[6] Brijain, M.; Patel, R.; Kushik, M.; Rana, K. A survey on decision tree algorithm for classification. Int. J. Eng. Dev. Res. 2014. Available online: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.673.2797 (accessed on 10 December 2021).

[7] Fix, E.; Hodges, J.L. Discriminatory analysis. Nonparametric discrimination: Consistency properties. Int. Stat. Rev. Int. De Stat. 1989, 57, 238–247. [CrossRef]

[8] Wright, R.E. Logistic regression. In Reading and Understanding Multivariate Statistics; American Psychological Association: Washington, DC, USA, 1995.

[9] Schapire, R.E. Explaining adaboost. In Empirical Inference; Springer: Berlin/Heidelberg, Germany, 2013; pp. 37–52. 10. Goodfellow, I.; Bengio, Y.; Courville, A. Deep Learning; MIT Press: Cambridge, MA, USA, 2016

[10] Malviya, R.K.; Kant, R. Green supply chain management (GSCM): A structured literature review and research implications. Benchmarking Int. J. 2015, 22, 1360–1394. [CrossRef]

[11] Fahimnia, B.; Sarkis, J.; Davarzani, H. Green supply chain management: A review and bibliometric analysis. Int. J. Prod. Econ. 2015, 162, 101–114. [CrossRef]

[12] Motwani, M.; Dey, D.; Berman, D.S.; Germano, G.; Achenbach, S.; Al-Mallah, M.H.; Andreini, D.; Budoff, M.J.; Cademartiri, F.; Callister, T.Q.; et al. Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: A 5-year multicentre prospective registry analysis. Eur. Heart J. 2017, 38, 500–507. [CrossRef]

[13] Gray, K.R.; Aljabar, P.; Heckemann, R.A.; Hammers, A.; Rueckert, D.; Initiative, A.D.N. Random forest-based similarity measures for multi-modal classification of Alzheimer's disease. NeuroImage 2013, 65, 167–175. [CrossRef] [PubMed]

[14] Mohan, S.; Thirumalai, C.; Srivastava, G. Effective heart disease prediction using hybrid machine learning techniques. IEEE Access 2019, 7, 81542–81554. [CrossRef]

[15] Lebedev, A.; Westman, E.; Van Westen, G.; Kramberger, M.; Lundervold, A.; Aarsland, D.; Soininen, H.; Kłoszewska, I.; Mecocci, P.; Tsolaki, M.; et al. Random Forest ensembles for detection and prediction of Alzheimer's disease

with a good between-cohort robustness. NeuroImage Clin. 2014, 6, 115–125. [CrossRef]
[16] Luz, E.J.d.S.; Nunes, T.M.; De Albuquerque, V.H.C.; Papa, J.P.; Menotti, D. ECG arrhythmia classification based on optimum-path forest. Expert Syst. Appl. 2013, 40, 3561–3573. [CrossRef]
[17] Challis, E.; Hurley, P.; Serra, L.; Bozzali, M.; Oliver, S.; Cercignani, M. Gaussian process classification of Alzheimer's disease and mild cognitive impairment from resting-state fMRI. NeuroImage 2015, 112, 232–243. [CrossRef]