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CirrhosisX: Detection and Staging of Liver Cirrhosis using DL and Explainable AI

Ms. Poonam Sadafal[1], Mansi Nirbhavane[2], Vinod Kumar[3], Nikita Nigude[4], Sharyu Nanware[5]

Assistant Professor, Department of Computer Engineering, Dr. D Y Patil College of Engineering & Innovation, Pune, India[1]

Student, Department of Computer Engineering, Dr. D Y Patil College of Engineering & Innovation, Pune, India[2]

Student, Department of Computer Engineering, Dr. D Y Patil College of Engineering & Innovation, Pune, India[3]

Student, Department of Computer Engineering, Dr. D Y Patil College of Engineering & Innovation, Pune, India[4]

Student, Department of Computer Engineering, Dr. D Y Patil College of Engineering & Innovation, Pune, India[5]

Abstract: Liver cirrhosis is a serious, ongoing health problem that leads to permanent harm in the liver from endless scarring and fibrosis. It hits hard on a global scale, being one of the top reasons people die around the world. Spotting it early and figuring out exactly how far along it is can really change things for patients, cutting down on the chances of more serious problems popping up.

This project introduces a hybrid approach to analyzing the MRI images of patients suffering from liver cirrhosis by using artificial intelligence methods. The DenseNet121 neural network is used to extract features from the medical images of patients, and this extracted information is then used to classify whether the patient is cirrhotic and at what stage this patient is cirrhotic. Not only does this method predict the likelihood of cirrhosis in a patient but also uses the Grad-CAM technique to visualize parts of the MRI images that help make these predictions.The performance of the system proposed herein is evaluated based on traditional performance indicators such as accuracy, precision, recall, and F1-scores.

In conclusion, the suggested approach can be used as an additional instrument that will help clinicians diagnose liver diseases and lessen their work.

Keywords: Liver Cirrhosis, Deep Learning, DenseNet121, XGBoost, Explainable AI, Medical Image Analysis, Grad-CAM, Hybrid Learning Model

INTRODUCTION

It is a chronic condition that involves gradual damage to healthy tissues due to scarring of liver tissues; consequently, the organ functions become impaired over time. There are many causes of this health problem, ranging from excess intake of alcohol to viral infections like hepatitis and metabolism disorders. At a more advanced stage, there are many complications associated with the condition, making timely diagnosis vital to ensure appropriate intervention strategies. Various tests and techniques are applied in the diagnostic process, including biopsy, blood tests, and imaging tests such as ultrasound, CT, and MRI. Among these, MRI is considered more popular since it offers detailed images of the liver and eliminates invasive procedures. Nonetheless, it demands high expertise to interpret findings, depending on the practitioner's experience. This might cause inconsistency, particularly while determining the stage of the disease.

With the progress of artificial intelligence technology, research into applying machine learning algorithms and deep learning algorithms to the field of medical image processing has attracted increasing attention. It was proven that convolutional neural networks (CNNs) have great strength when it comes to extracting complicated features from image data. They can contribute to disease detection and diagnosis, improving accuracy and reducing the workload.

However, there is one significant drawback regarding deep learning algorithms – their interpretability. The interpretability factor is essential in medical cases since it is necessary for a physician to know the logic behind the model's decisions. That problem was solved by developing a technique known as XAI – explainable artificial intelligence. One example of such a technique is called Grad-CAM – gradient-weighted class activation mapping.

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In this study, a fusion method has been suggested for detecting and classifying liver cirrhosis with the use of MRI images. For this purpose, DenseNet121 is employed for feature extraction, and XGBoost classifier is employed for classification. Furthermore, Grad-CAM is incorporated for better interpretability and understanding of the model predictions. The ultimate aim of this research is to design a model that can assist healthcare professionals in their diagnosis process.

LITERATURE REVIEW

Savaş (2025) introduced a clever stacked ensemble learning approach that merges convolutional neural networks (CNNs) with XGBoost to predict and assess the stages of liver cirrhosis from MRI scans. The findings were top-notch, with accuracy hitting about 97% for both straightforward yes/no calls and more detailed multi-level groupings. What made it stand out was using Grad-CAM to pinpoint the exact liver spots that shaped the predictions, showing how clear visual aids can build confidence in AI results for medical pros.

Along similar lines, Noor et al. (2025) created a deep neural network that optimized features through methods like PCA, LDA, and ReliefF, tested on the ILPD dataset. Their tool reached over 90% accuracy and applied SHAP values to clarify which clinical details—such as bilirubin, albumin, and ALT levels—played the biggest roles in diagnoses. This mix of strong results and easy-to-follow explanations turned their model into something both high-performing and practical for real clinics.

A comprehensive review by Noor A. A. et al. (2025) examined close to 89 papers from 2000 to 2024 on explainable AI in healthcare. They observed that deep learning delivers great accuracy, but most systems remain mysterious black boxes. The team stressed the importance of common standards and data pools to encourage openness, which directly backs our paper's goal of crafting a model that unites precision with clear insights.

Njei et al. (2024) put forward an explainable machine learning setup using XGBoost, SHAP, and LIME to forecast how liver conditions might worsen. Their research showed how these tools can highlight key factors, like enzyme and bilirubin levels, providing doctors with sharper views into patient paths.

Luetkens et al. (2022) used a deep learning model on MRI images to spot and evaluate liver fibrosis. It scored an outstanding AUC of 0.94, proving deep CNNs can handle the intricate patterns of scarring in cirrhosis. They also confirmed that adjusting models like U-Net and ResNet works wonders for accurately outlining the liver.

Kumar et al. (2023) brought in an enhanced ResNet with attention features for catching cirrhosis, boasting high sensitivity and specificity. Their work noted that borrowing techniques from models like MobileNetV2 or ResNet18 makes training smoother, even with small amounts of medical data.

Lastly, Noor et al. (2025) in the *Diagnostics Journal* explored explainable AI in liver care. They explained how Grad-CAM and SHAP make model choices easier to understand, fostering trust in clinicians. This reinforces why straightforward AI is essential in medical fields.

PROPOSED METHODOLOGY

The suggested methodology follows a pipeline-like structure with two stages. The first step involves feeding the MRI images into the DenseNet121 neural network. Rather than utilizing the output of the classification layer, the embedding of the images was acquired at the intermediate layer to make sure that the model pays attention to the structural features of the liver.

At the next stage, the extracted features of the images are concatenated with the clinical features, resulting in a joint representation of the patient’s medical record. Then, the obtained representation is fed to the XGBoost model, where the tasks of detection and staging of HCC are executed. The hyperparameters of the XGBoost algorithm have been set empirically.

It has been found that the suggested method offers improved stability and generalization compared to the use of a pure deep learning

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A. System Architecture Overview

The general system architecture can be seen as a linear pipeline, transforming raw medical images into useful predictions. The pipeline starts with pre-processing of the image in order to have high-quality medical images of a fixed size.

Once the image processing phase is completed, the next step involves feeding the image to a deep learning network for feature extraction. Then the extracted features are fed along with the available clinical data for generating better representations of the medical situation.

The generated representations are finally provided to the machine learning model for predicting the cirrhosis presence along with its level. Explainable AI is used for producing visual representations of the decisions made by the model.

Overall Pipeline:

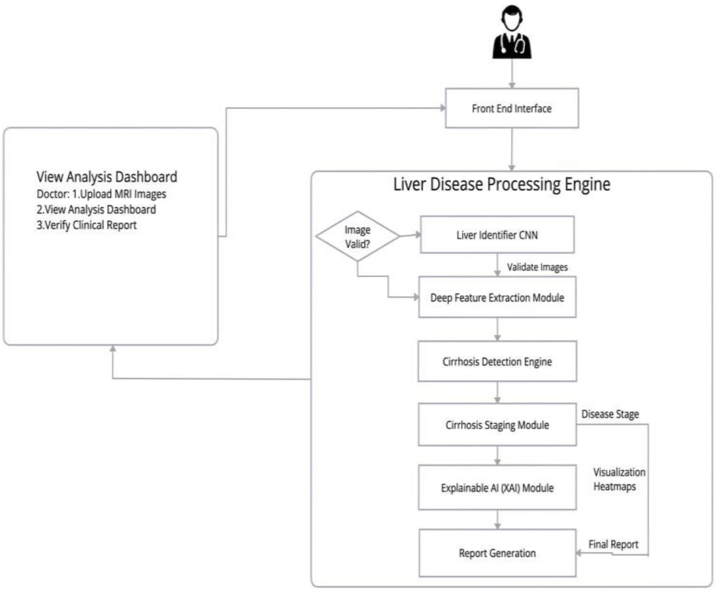

Fig.1**.** System architecture of the proposed explainable AI-based liver cirrhosis detection and staging framework.

This modular architecture enables efficient learning while maintaining flexibility for future clinical integration.

B. Image Preprocessing and Data Preparation

The MRI datasets vary greatly from one another in terms of resolution, level of noise, and intensities. Therefore, preprocessing was done before training the model.

The first step was to resize all images to a specific size that suits the DenseNet121 model. Furthermore, intensity normalization was done to ensure consistency in the intensity level of all images. Moreover, image augmentation, which includes rotation, flipping, and zooming of the images, was also done.

This allows the model to perform better.

C. Deep Feature Extraction Using DenseNet121

The model chosen for feature extraction from the MRI images is the DenseNet121. It was chosen for its efficient architecture, where information is shared between layers, enabling it to learn better than other convolutional neural networks.

Transfer learning was used to maximize the utilization of the data available. In this case, a pre-trained set of weights for a large dataset was used to train the model on the medical dataset.

Rather than using the final layer that outputs predictions, the feature vectors were extracted from the middle layers of the model. The features correspond to various textures, structural abnormalities, and fibrosis symptoms of the liver that are essential in diagnosing and staging cirrhosis.

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D. Feature Fusion and XGBoost Classification

For better predictive outcomes, the extracted features from the MRI scans were merged with the clinical features that characterize the patient's health status. The resulting feature fusion represents a holistic description of the liver's health. The fused feature sets were employed as inputs for the XGBoost classifier. This approach was selected due to the effectiveness of the algorithm in working with structured data and accounting for the complexity of feature interactions. The classifier is designed to detect not only the occurrence but also the stage of cirrhosis development. The classifier makes improvements by learning from mistakes iteratively, with each iteration focusing on correcting previous errors.

E. Explainable Artificial Intelligence Using Grad-CAM

Explanation of how the model arrives at a decision is crucial, particularly for the application of the model in medical purposes. The model relies on Grad-CAM to identify the regions of an MRI image that play a major role in generating the output.

The output heat maps indicate certain regions of the liver involved in the final decision-making process. Typically, these regions are significant anatomical parts of the liver associated with cirrhosis.

The visualization helps in verifying that the model pays attention to relevant areas in the liver.

F. Implementation Environment

This model was built using Python as the main programming language. The deep learning modules were implemented using TensorFlow and Keras libraries, whereas the classification module was done using XGBoost. Preprocessing of images and processing data were accomplished using OpenCV and NumPy libraries.
Training was done in a GPU environment, which decreased training time.

G. Tools and Technologies

We're building this AI model for diagnosing liver cirrhosis using MRI scans and clinical data, and we've chosen Python 3.8 or later as our go-to programming language. It's incredibly flexible and has fantastic support for all the machine learning and deep learning tools we need.

At the heart of our deep learning work, we're using **TensorFlow** and **Keras** to create and train **Convolutional Neural Networks (CNNs)** like **DenseNet121**. These models excel at segmenting and classifying images, striking a great balance between high accuracy and reasonable computation time. For the staging part—predicting how severe the liver cirrhosis is—we're bringing in **XGBoost**, which smartly combines features from the images with clinical parameters to make those predictions.

To handle all the data prep, we rely on **NumPy**, **Pandas**, and **scikit-learn**. They help us scale, encode, and clean up our datasets effectively. **OpenCV** comes in handy for enhancing, resizing, and augmenting the MRI images, making our model more resilient to the natural variations in scans.

Trust is key in medical AI, so we've integrated **Grad-CAM (Gradient-weighted Class Activation Mapping)** to explain the model's decisions. Grad-CAM provides visual heatmaps showing what the model is focusing on in the images.

For deployment, we're using **Flask** as our micro-framework, paired with a front-end built in **HTML**, **CSS**, and **Bootstrap**. This lets users easily upload MRI images and check out the diagnostic results through a clean, interactive web interface.

The whole system runs smoothly on a workstation with **8–16 GB of RAM** and an **NVIDIA GPU with 6–8 GB of VRAM**, giving us plenty of power for training, testing, and making real-time predictions.

H. Expected Outcome

Imagine we're building this AI-powered tool that can spot and measure the severity of liver cirrhosis more accurately and openly than ever before. The goal is to help doctors make smarter choices by blending what they see in images with patient data, and the AI explains its reasoning step by step so everyone understands why it made a certain call. Down the line, this could be the foundation for even better medical systems that focus on getting things right while being crystal clear, ultimately leading to safer and more reliable healthcare for patients.

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CONCLUSION

Our proposed system feels like a real game-changer for tackling liver cirrhosis—a condition that can sneak up on people and turn lives upside down. We've crafted an intelligent, explainable tool that predicts, detects, and stages it all in one go, using a multi-modal, patient-level approach that treats each person as a whole story, not just a set of data points. By weaving together MRI images, lab results, and clinical details, we get spot-on classifications into Normal, Mild, Moderate, or Severe stages, giving doctors a clear, actionable picture without the guesswork.

What really sets it apart is the transparency: Grad-CAM lights up the key spots on those MRI scans, while SHAP breaks down how lab values or lifestyle factors tipped the scales. And with decision-level fusion in the mix, it's not just accurate—it's reliable in the messy reality of clinical practice. Ultimately, this bridges the divide between fancy research and everyday medicine, delivering a trustworthy AI sidekick that helps diagnose liver disease with confidence. Imagine doctors feeling empowered, patients getting clearer answers, and better outcomes all around.

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