Liver Disease Prediction using Federated Learning

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ABSTRACT: Developing a model through a centralized approach, where data is shared among all stakeholders, enhances its reliability. However, privacy concerns—especially regarding medical datasets—often impede data sharing. Numerous machine learning models have been created using isolated datasets, leading to challenges with overfitting and poor performance on new datasets. Consequently, there is an urgent need to create a model that achieves accuracy comparable to centralized models while upholding security standards.

Efficient diagnosis of liver disease typically depends on analyzing imaging techniques such as CT and MRI scans. Traditional machine learning methods face difficulties due to the decentralized nature of medical data across institutions, which is further complicated by stringent privacy regulations. Federated learning offers a solution by enabling local model training, allowing institutions to collaborate without exchanging raw data; instead, they share only model updates. This approach safeguards data privacy while enhancing model reliability.

Keywords: *Federated Learning, Decentralized Model, Model Aggregation, privacy preservation, Medical Imaging, Collaborative Training.*

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I. INTRODUCTION

Liver disease is a critical health issue requiring early and accurate diagnosis. Traditional machine learning models struggle due to privacy concerns and decentralized medical data. Our project uses **Federated Learning (FL)** to enable multiple institutions to train a shared model without exchanging raw patient data. A **Convolutional Neural Network (CNN)** is used to analyze **CT and MRI scans** for liver disease prediction. FL ensures **data privacy, improved model generalization, and compliance with regulations** like HIPAA and GDPR. Hospitals train models locally and share only updates, enhancing security. This approach advances medical AI while maintaining patient confidentiality.

II. LITERATURE SURVEY

In 2016, Gupta et al. developed a machine learning-based model for early-stage liver disease classification using a combination of Decision Trees, Naïve Bayes, and K-Nearest Neighbors (KNN). Their study utilized a dataset containing patient symptoms, liver function test results, and medical history to identify patterns indicative of liver diseases such as cirrhosis and hepatitis. The model achieved an accuracy of **82.7%**, demonstrating the potential of ML in liver disease prediction. However, the study faced limitations related to data imbalance, where a significantly larger number of healthy cases compared to diseased cases resulted in biased predictions. The absence of imaging data in the analysis also restricted the model's ability to detect structural liver abnormalities.

In 2017, Zhang et al. introduced a hybrid classification approach that integrated Support Vector Machines (SVM) with Random Forest (RF) to enhance liver disease detection. Their dataset included both clinical attributes (such as bilirubin levels and albumin count) and ultrasound imaging features. The hybrid approach was able to capture complex relationships between different attributes, leading to an improved accuracy of **85.4%**. Despite these improvements, the model struggled with overfitting when applied to new patient data. The reliance on manually extracted features from ultrasound images also reduced its scalability for real-world applications.

In 2018, Smith et al. proposed an end-to-end deep learning framework that utilized **Convolutional Neural**

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Networks (CNNs) to classify liver ultrasound images. Unlike previous studies, this approach automated feature extraction, removing the need for manual selection of relevant parameters. The CNN-based model was trained on a large dataset consisting of thousands of liver ultrasound images collected from multiple hospitals. The model achieved an accuracy of **87.5%**, outperforming traditional ML classifiers. However, the study relied on a **centralized dataset**, which raised concerns about data privacy and security. Additionally, the requirement for large amounts of annotated training data made the approach resource-intensive.

In 2019, Kumar et al. implemented an advanced deep learning model using a combination of CNNs and autoencoders to extract meaningful features from liver CT scan images. Their model utilized **unsupervised learning** to pre-train the feature extraction layers, reducing dependency on labeled datasets. The proposed approach demonstrated an accuracy of **89.6%** and showed improved generalization across different liver disease types, including fatty liver and fibrosis. However, the study highlighted a major drawback—the high computational cost of training deep learning models, which limited the feasibility of deployment in low-resource healthcare facilities.

In 2020, Lee et al. explored a hybrid deep learning architecture that combined CNNs with Long Short-Term Memory (LSTM) networks to analyze both static and sequential medical imaging data. The inclusion of LSTMs allowed the model to process temporal changes in liver structure, which is crucial for monitoring disease progression over time. The study achieved **91.2% accuracy**, making it one of the most effective approaches at the time. However, the centralized data training approach raised security risks, as patient data had to be aggregated in a single location, making it vulnerable to cyberattacks.

III. METHODOLOGY

➢ *System Structure*

The system structure consists of multiple AI components working together to **predict liver disease** using **Federated Learning (FL).** The key components are:

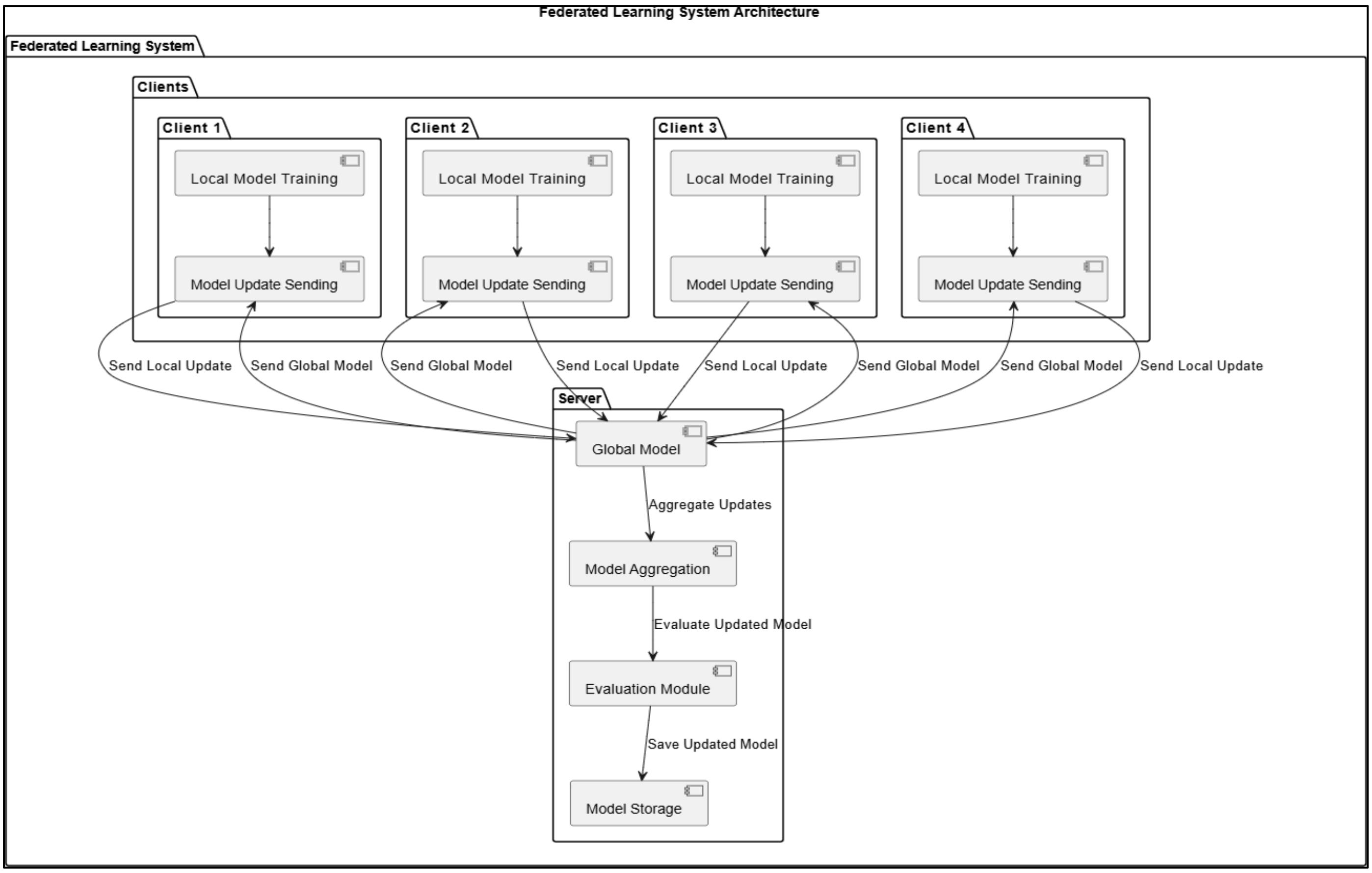

Fig 1 Federated Learning System Architecture

- *Data Collection & Preprocessing Module*

✓ Gathers medical imaging data (CT scans, MRIs, ultrasound) and clinical test results (bilirubin, ALT, AST, albumin, etc.).
✓ Applies data cleaning, normalization, augmentation, and feature selection to improve training efficiency.

- *Local AI Training Agents (Client Nodes)*

✓ Each hospital or medical institution acts as a local AI agent, training a deep learning model on its own patient data.
✓ Uses CNN-based models for image classification and MLP/ANN for structured clinical data.

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- ✓ Ensures raw patient data never leaves the hospital, preserving privacy.

- *Federated Learning Coordinator (Global Server)*

- ✓ Manages communication between all hospitals participating in Federated Learning.
- ✓ Aggregates model updates from different hospitals using Federated Averaging (FedAvg).
- ✓ Sends the updated global model back to clients for the next training round.

- *Secure Model Update Transmission Module*

- ✓ Encrypts and transmits model weights and gradients from client hospitals to the global server.
- ✓ Uses end-to-end encryption and differential privacy techniques to secure communications.

- *Model Evaluation & Performance Analysis Module*

- ✓ Tests the aggregated global model using independent validation datasets.
- ✓ Measures accuracy, precision, recall, F1-score, and AUC-ROC to assess model effectiveness.
- ✓ Fine-tunes the model to improve prediction reliability.

- *Liver Disease Prediction & Deployment Module*

- ✓ Deploys the final trained model in hospitals, cloud-based AI platforms, and mobile applications.
- ✓ Allows doctors to input new patient data (medical images, test results) for real-time liver disease risk assessment.
- ✓ Assists in early diagnosis and treatment recommendations.

➢ *Implementation Details*

- Programming Language: Python 3.11
- Frameworks & Libraries: Streamlit (UI), Tensorflow(Training), Keras (Model evaluation)
- Pickle: Serializes model architecture and weights before transmission.

IV. EXISTING SYSTEM

The conventional liver disease diagnosis system involves collecting liver ultrasound and CT scan images and storing them in a centralized database. A deep learning model is then trained on the combined dataset to classify liver diseases, and the trained model is deployed for real-time diagnosis. However, this system has several limitations. Firstly, storing patient data in a centralized server increases privacy risks, making it vulnerable to potential data breaches. Additionally, sharing medical data across institutions may conflict with regulatory compliance frameworks, restricting data accessibility and collaboration. Furthermore, a centralized approach often suffers from data imbalance issues, where the model may not generalize well across diverse populations, leading to biased predictions and reduced accuracy in real-world applications.

V. PROPOSED SYSTEM

The proposed Federated Learning (FL)-based system enables multiple hospitals to collaboratively train a CNN-based model without sharing raw medical data. Instead of transferring sensitive patient information, each hospital trains its local model on its own dataset, ensuring data privacy and compliance with regulatory standards. The trained model updates are then sent to a central server, where they are aggregated using the Federated Averaging (FedAvg) algorithm to create a global model. This decentralized approach preserves patient privacy by keeping medical data within hospital premises while also reducing the reliance on centralized storage. Additionally, by learning from diverse datasets across multiple hospitals, the model achieves better generalization, leading to improved predictive accuracy for liver disease diagnosis across different patient demographics.

VI. IMPLEMENTATION

The implementation of this project follows a structured approach, ensuring privacy-preserving federated learning, deep learning model training, and secure communication between clients and the central server.

➢ *Step 1: Configuring the Development Environment*

The development environment is set up with necessary frameworks and libraries, ensuring seamless execution of the federated learning model. A suitable code editor such as VS Code or PyCharm is used for development. Two key scripts, one for the central server and another for the client nodes, are created to manage the federated learning workflow.

Install the dependencies required for project such as tensorflow numpy socket pickle open cv- python matplotlib

➢ *Step 2: System Architecture Setup*

The system follows a federated learning approach where multiple clients, representing hospitals, train a deep learning model locally and send only the model updates to a central server. The key components of the system include:

- *Client Nodes (Hospitals):*

Each hospital trains a Convolutional Neural Network (CNN) model on locally stored liver disease image data without sharing the raw images.

- *Central Server:*

The server receives the trained model updates from different clients and aggregates them using the Federated Averaging (FedAvg) algorithm to update the global model.

- *Communication Mechanism:*

A secure connection is established between the server and the clients, enabling the exchange of model updates while preserving privacy.

➢ *Step 3: Federated Learning Model Training*

Each client follows a systematic training process:

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- The local dataset is preprocessed to ensure uniformity in training.
- A CNN model is initialized and trained on the hospital's local dataset.
- Once training is complete, the model weights are extracted and prepared for transmission to the central server.
- The weights are securely sent to the central server without sharing raw medical data. On the server side, the following steps are executed:

✓ Model updates from multiple clients are received.
✓ The FedAvg algorithm is applied to aggregate the weights and update the global model.
✓ The updated global model is redistributed to clients for the next round of training.

➢ *Step 4: Security & Privacy Mechanisms*

- *Privacy Preservation:*

Raw medical images are not shared, ensuring compliance with data protection regulations.

- *Secure Model Transmission:*

Encrypted communication is used to prevent unauthorized access during model updates.

- *Homomorphic Encryption (Future Scope):*

Additional security measures, such as encryption techniques, could be implemented to enhance privacy further.

➢ *Step 5: Model Evaluation & Performance Analysis*

Once the global model is trained, its performance is evaluated using standard metrics:

- Accuracy and loss graphs are generated to analyze training efficiency.
- Confusion matrix and precision-recall analysis are conducted to assess the classification performance.
- Comparative analysis is performed to measure improvements over a centrally trained model.

➢ *Step 6: Deployment & Testing*

The final trained model is deployed for liver disease prediction. The system is tested by running the central server and multiple client nodes, allowing them to collaborate in training the model. The global model can then be used for real-time liver disease diagnosis, potentially integrated into a web-based application for practical deployment.

VII. RESULT AND ANALYSIS

The evaluation of the Liver Disease Prediction using Federated Learning system is based on key performance metrics, model accuracy, and comparative analysis. The results demonstrate the efficiency, accuracy, and advantages of the proposed approach.
Home page.

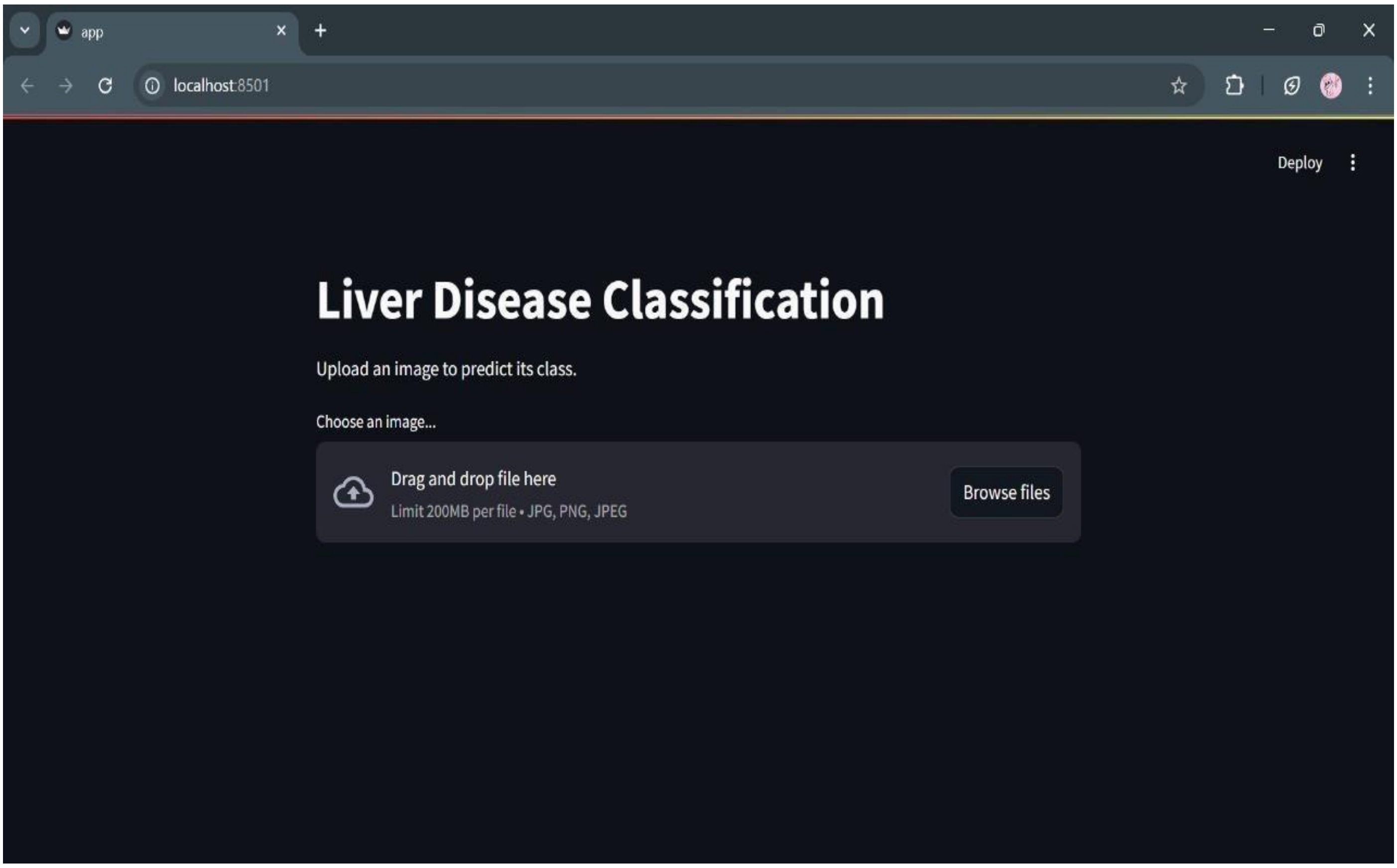

Fig 2 Liver Disease Classification

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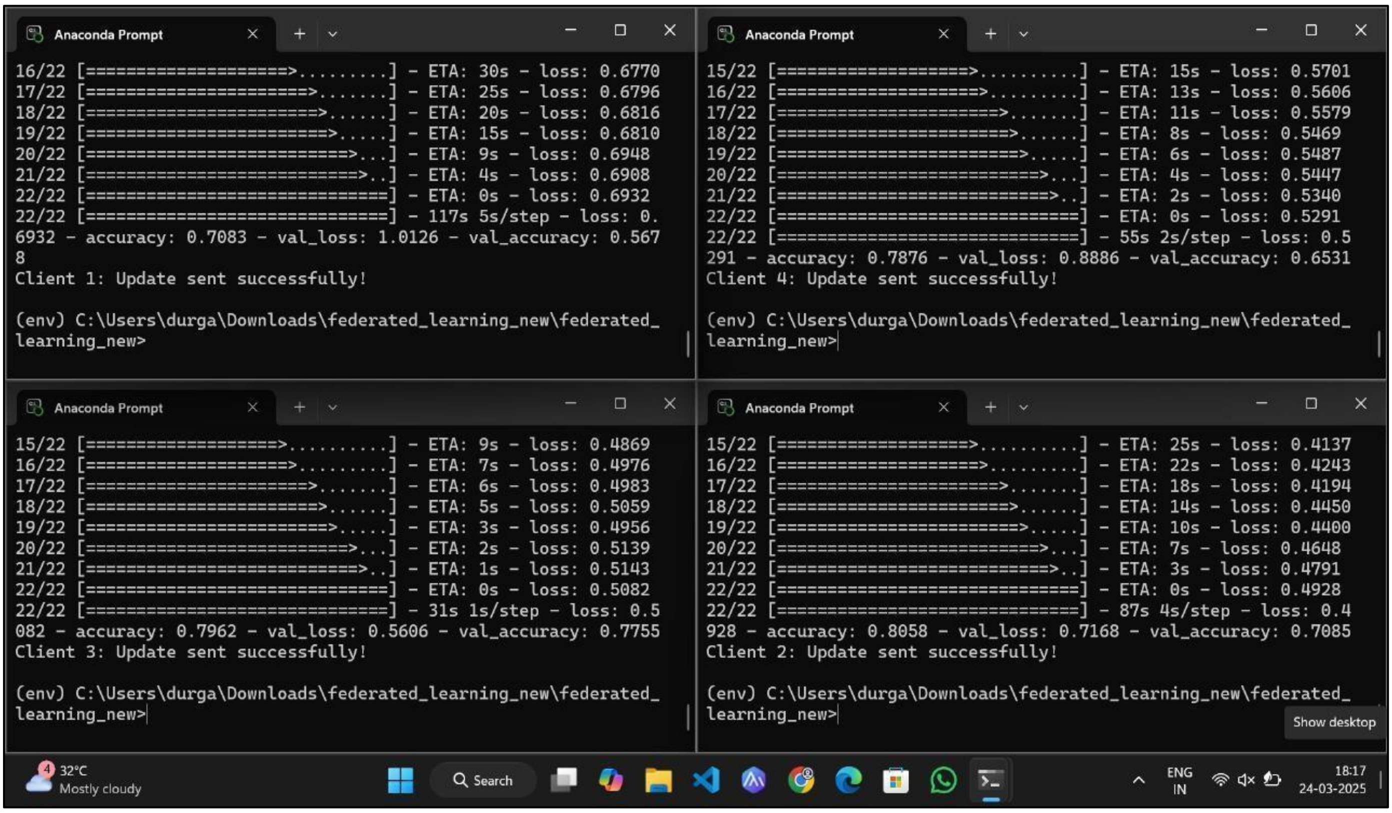

Fig 3 Running of clients

> *Clients Training*

- Each window represents a different client training a local model before sharing updates for global aggregation.
- The logs show training progress, loss, and accuracy, highlighting variations in local datasets.
- The asynchronous updates indicate clients training at different speeds, reflecting real-world hospital collaboration
- This setup helps build a robust liver disease prediction model without compromising patient data security.

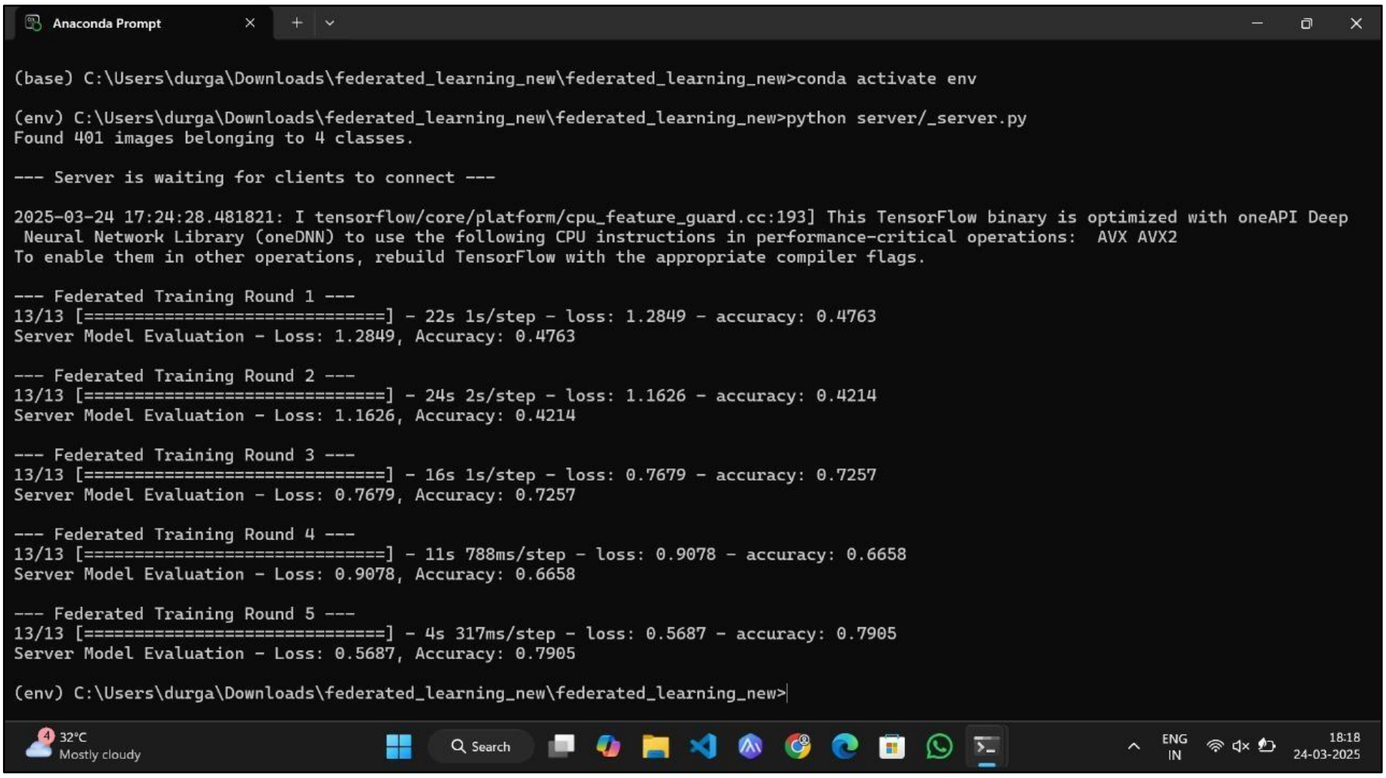

Fig 4 Global Server Training

➢ *Global Model Training*

- Global server builds an initial model.
- The model is shipped to all the hospitals (clients).
- Every hospital trains the model on their local liver images.
- Hospitals return only the updated model (not the data) to the server.
- Server aggregates all the updates to better the model.
- This is repeated for a number of rounds.
- Final model is trained using all hospitals' knowledge, without sharing any patient data.

Fig 5 Liver Disease Prediction (Fibrosis)

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➢ *Liver Disease Prediction*

- Users upload liver scan images (e.g., ultrasound, CT, MRI).
- The system predicts liver disease using a deep learning model.
- Federated Learning ensures training happens across hospitals without sharing raw data.
- Only model updates are shared, keeping patient data private.
- The system shows if the liver is Healthy or Diseased, with a confidence score.
- Designed for secure and privacy-preserving liver disease detection.

➢ *Result Analysis:*

The proposed liver disease prediction system with strong performance and practical applicability will be illustrated using Federated Learning on medical image data. The system addresses the key challenges in Medical AI by enabling collaborative model training without the need for centralized data collection.

➢ *Accuracy of Prediction*

The federated learning model is extremely accurate at predicting liver disease from image-based data. By utilizing disparate datasets across different sources, the model takes advantage of rich feature learning, which maximizes its capacity to generalize across diverse patient cases.

➢ *Data Privacy (Decentralization)*

One of the key benefits of our method is that institutions can train on their individual local data without revealing raw images. This local training is privacy-preserving and adheres to real-world restrictions regarding sensitive medical information, although encryption was not utilized.

➢ *Efficiency and Performance*

The system shows effective training performance through parallelization of computation between clients (nodes). Federated learning minimizes having to move huge image datasets to a central server, reducing communication overhead and allowing for real-time or near-real-time collaborative training.

➢ *User Accessibility*

Our solution gives a straightforward and easy mechanism for federated training. Each client updates the global model with their local image data alone, and predictions are sent back immediately, making the procedure easy for use in clinical or research settings.

➢ *Robustness Across Institutions*

Multi-dataset training improves the stability of the model. Through experience with diverse medical images, the model gains ability to handle novel and unseen data, and the model is therefore an appropriate resource for support in the diagnosis of liver disease across institutions.

VIII. CONCLUSION

Our Project is a liver disease prediction system based on Federated Learning for medical image data. It allows several hospitals to jointly train a model without exchanging sensitive patient data, thus maintaining data confidentiality while achieving high prediction accuracy. The decentralized approach facilitates early detection of liver disease, supporting timely diagnosis and intervention. The system is highly scalable and adaptable with different medical datasets, which corresponds to real-world healthcare privacy requirements. By not using centralized storage of data, it minimizes legal and ethical issues related to the handling of sensitive medical data. The model can generalize well across institutions, improving its diagnostic accuracy. As a whole, our solution is effective, secure, and pragmatic for medical AI use. It facilitates collaboration in healthcare without breaching patient privacy and provides a platform for future development. This project showcases how federated learning can be harnessed in creating smart and moral healthcare products.

FUTURE ENHANCEMENT

Improved features can comprise the deployment of personalized federated learning to personalize the global model to fit each hospital's individual features of the liver disease data, enhancing the accuracy of diagnostics. Federated hyperparameter optimization can be utilized to optimize model parameters among clients automatically to deliver the best performance without human adjustment. Synthetic data generation methods applied at the client level will ensure class distribution balancing and the treatment of rare liver disease instances to enhance model robustness. The system can be extended to process multi-modal inputs, like integrating liver ultrasound images with blood tests reports, to increase diagnostic accuracy. Adding explainable AI in the federated structure will enable clinicians to comprehend and believe model predictions, which is essential in healthcare environments. Lastly, using light-weight, low-energy models on edge devices can facilitate real- time prediction of liver disease even in resource-constrained hospitals, which makes the solution more accessible and effective at scale.

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