# Revolutionizing Liver Care: Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques

#### 1. Introduction

**Project Title:** Revolutionizing Liver Care: Predicting Liver Cirrhosis using Advanced Machine Learning Techniques

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**Team Size: 5** 

- Team Leader: V Mounika Jaya Project Coordination, Milestone Tracking, Model Building, Final Validation
- Team Member: Modhukuru Kavya Data Collection, Cleaning, preprocessing pipeline
- Team Member: M Sanjana Define Problem /Problem Understanding
- Team Member: G Chandana ML Model Development & Flask Integration
- Team Member: Gaddam Lakshmi Bindhu UI/UX Design, Documentation, Descriptive Statistics

# 2.Project Overview

#### 2.1. Purpose

Liver cirrhosis is a critical health concern globally, leading to chronic liver failure and high mortality rates. This project aims to build a machine learning model to predict liver cirrhosis based on various patient features. By analysing these features, the model will classify patients into risk categories, aiding in early diagnosis and treatment.

#### 2.2. Features

- User input form with 41 clinical features
- Prediction using a trained Random Forest model
   Result displayed in a user-friendly web interface
- Error handling for missing or invalid data.
- Instantly returns a prediction label "Likely Cirrhosis" or "Not Likely Cirrhosis" – after form submission.

#### 3. Architecture

#### 3.1. Frontend

- Developed using HTML5, CSS3, and Jinja2 templates.
- HTML form (index.html) for inputting 41 patient features
- Styled using embedded CSS and images served from the /static directory
- Features a clean, responsive UI with gradient backgrounds and conditionally rendered prediction results.

#### 3.2. Backend

- Backend logic implemented using Python and Flask
- Model Training Pipeline:
- Model training, evaluation, and export handled in Google Colab.
- Scripts for data cleaning, feature engineering, and training were executed in Colab.
- Final .pkl files (model + tools) were trained and exported in Colab, then used in the Flask backend for real-time predictions.
- Model:

A Random Forest Classifier trained on a liver health dataset. Model artifacts include:

- liver prediction.pkl: Trained model
- label encoders.pkl: LabelEncoder instances
- normalizer.pkl: MinMaxScaler instance

#### 3.3. Data Preprocessing:

- Normalization with MinMaxScaler
- Label Encoding for categorical variables
- Blood pressure parsing and transformation
- Encoders and scalers saved as .pkl files

#### 3.4. Database

- No persistent database is used
- Prediction is done entirely in-memory based on form input

## 4. Setup Instructions

#### 4.1. Prerequisites

- Python 3.10+
- Flask
- scikit-learn
- · pandas, numpy
- Google Colob (or Jupyter Notebook)

#### 4.2. Installation

install -r requirements.txt

#### 5. Folder Structure

#### **5.1. Client (Flask Frontend)**

The frontend is handled via HTML templates and static assets:

- The index.html file contains a full HTML form with 41 input fields styled with CSS.
- Static assets like background images and CSS files are stored in the static/ folder.

#### 5.2. Server (Flask Backend)

The backend is built using Python and Flask:

```
    — app.py # Flask application script
    — train_model.py # Script for preprocessing data and training ML model
    — liver_prediction.pkl # Trained Random Forest model
    — normalizer.pkl # Saved MinMaxScaler
    — label_encoders.pkl # Dictionary of saved label encoders
    — Liver.ipynb # Notebook for model development and training in Colab
```

- app.py handles routing, data preprocessing, and prediction logic.
- train model.py processes the dataset, trains the model, and saves necessary artifacts.
- .pkl files are used to load the model and preprocessing tools during prediction.

# 6. Running the Application

• Start the app:

cd Flask

python app.py

• Open in browser at: <a href="http://127.0.0.1:5000/">http://127.0.0.1:5000/</a>

#### 7. API Documentation

This is a form-based app. However, the /predict route accepts POST requests from the form and returns an HTML page with the prediction result. *POST* /

- **Route**: / (root URL)
- · Method: POST
  - Inputs: 41 clinical features submitted through the HTML form, such as:
  - Age
  - Alcohol Type
  - Blood Pressure
  - AST, ALT, Bilirubin
     Liver enzyme levels, etc.
  - Processing:
  - Input is encoded using label encoders.pkl
  - Numerical values are normalized using normalizer.pkl
  - The processed data is passed into the liver\_prediction.pkl model for prediction
  - Output:
  - Rendered HTML page (index.html) showing:
  - Prediction result: "Likely Cirrhosis" or "Not Likely Cirrhosis"
  - Visual indication (color-coded message with icon)
  - Error Handling:
  - Displays a friendly error message for missing/invalid inputs o
     Handles issues like blood pressure format (e.g., 120/80)

#### 8. Authentication

Not applicable – This application does not implement user login or authentication as it's a prototype for medical prediction.

#### 9. User Interface

- Form with 40+ inputs related to demographics, lifestyle, blood work, and liver panel.
- Background with a semi-transparent liver theme.
- Health vs Warning output with icons and color-coded messages.

# 10. Testing

- Model accuracy was validated using scikit-learn.
- Manual testing of form inputs and blood pressure parsing.

• Model tested against holdout test data with stratified split (80/20).

# 11. Screenshots or Demo

• This form collects patient data such as age, alcohol intake, and liver function markers

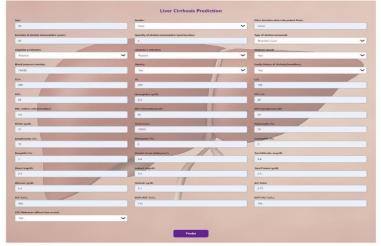


Figure 11.1: Sample Form Filled

• A green success box appears indicating low or no risk.



Figure 11.2: Prediction Result - Likely Cirrhosis

• A red alert box appears indicating high risk of liver cirrhosis.



Figure 11.3: Prediction Result - Not Likely Cirrhosis

• The terminal shows Flask running, and incoming form data logged.

```
## Classification Report:

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Figure 11.4: Backend Terminal Output

#### • Demo Link:

https://drive.google.com/file/d/1QhDMlD8jW6paeBegi\_yCfrNAg4wDDyXC/view?us p=drive link

### 12. Known Issues

- Strict blood pressure format required (e.g., 120/80)
- No database or session tracking
- Limited interpretability of ML model predictions

# 13. Future Enhancements

- Add database to store patient inputs and predictions.
- Provide downloadable PDF reports of results.
- Improve model accuracy with a larger and more balanced dataset.
- Integrate with hospital systems for real-time screening.
- Add user registration, patient history tracking, and mobile responsiveness.