1. Introduction

1.1. Project Overview

This project focuses on developing a machine learning model to predict liver cirrhosis based on patient health data. The goal is to provide a tool for early detection and diagnosis to aid in timely medical intervention.

1.2. Objectives

- To collect and preprocess patient health data.
- To explore and analyze the data to understand key features.
- To develop and evaluate different machine learning models.
- To optimize and tune the selected model for better performance.
- To integrate the model into a web application for easy accessibility.

2. Project Initialization and Planning Phase

2.1. Define Problem Statement

The problem is to predict whether a patient is suffering from liver cirrhosis based on various health metrics and historical data.

2.2. Project Proposal (Proposed Solution)

The proposed solution is to develop a machine learning model using Logistic Regression, along with other classifiers for comparison. The final model will be integrated into a web application using Flask for easy user access.

2.3. Initial Project Planning

The project will be divided into multiple phases: data collection and preprocessing, model development, model optimization and tuning, and final deployment. Each phase will have specific tasks and milestones.

3. Data Collection and Preprocessing Phase

3.1. Data Collection Plan and Raw Data Sources Identified

Data will be collected from various medical records and publicly available health datasets. The raw data sources are:

Section	Description

Project Overview	This machine learning project aims to develop a predictive model for liver cirrhosis. The objective is to utilize patient data, including demographics, medical history, and lab results, to predict the likelihood of liver cirrhosis. The model will help in early diagnosis and improve treatment outcomes.
Data Collection Plan	The data will be collected from various sources, including public healthcare datasets, private hospital records, and online medical repositories. Specific details about each source, including access permissions and data formats, are outlined in the Raw Data Sources Template.
Raw Data Sources Identified	A comprehensive list of raw data sources has been identified, each described with relevant details such as location, format, size, and access permissions

Raw Data Sources Template

Source Name	Description	Location/URL	Format	Size	Access Permissions
Dataset 1	Public healthcare dataset containing demographic and medical data of patients.	Healthcare Dataset	CSV	2 GB	Public

3.2. Data Quality Report

The data will be assessed for quality issues such as missing values, duplicates, and inconsistencies. Missing values will be handled using appropriate imputation techniques, and duplicates will be removed.

Data Source	Data Quality Issue	Severity	Resolution Plan
Dataset	There is a feature named ‘AG Ratio’ in which a single column contains different data types, such as string and float values	Low	Converted the strings(which are denoted in ratio format) into float values

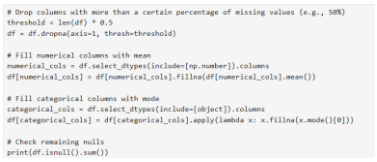
3.3. Data Exploration and Preprocessing

The data will be explored using univariate, bivariate, and multivariate analyses. Preprocessing steps will include handling missing data, transforming variables, feature engineering, and normalizing the data.

Section	Description
Data Overview	The data overview provides basic statistics, dimensions, and structure of the dataset. It includes the number of records, number of features, and data types of each feature
Univariate Analysis	Univariate analysis involves exploring individual variables to understand their distribution, central tendency (mean, median, mode), and dispersion (variance, standard deviation). Visualizations such as histograms and box plots are used to illustrate these statistics
Bivariate Analysis	Bivariate analysis examines the relationship between two variables. This includes calculating correlation coefficients and creating scatter plots to visualize potential linear or non-linear relationships between pairs of variables
Multivariate Analysis	Multivariate analysis explores patterns and relationships involving multiple variables simultaneously. Techniques such as principal component analysis (PCA) and multiple regression analysis are employed to understand the interactions between variables

Outliers and Anomalies	Identifying and treating outliers is crucial to ensure accurate analysis. This section involves detecting outliers using statistical methods (e.g., IQR, Z-scores) and deciding on appropriate treatments (e.g., removal, transformation)
Data Preprocessing Code Screenshots	

Loading Data	`#Reading csv file`
	`df = pd.read_csv('HealthCareData.csv')`
	`df.head()`

Handling Missing Data	
	`# Drop columns with more than a certain percentage of missing values (e.g., 50%)`
	`threshold = len(df) * 0.5`
	`df = df.dropna(axis=1, thresh=threshold)`
	`# Fill numerical columns with mean`
	`numerical_cols = df.select_dtypes(include=[np.number]).columns`
	`df[numerical_cols] = df[numerical_cols].fillna(df[numerical_cols].mean())`
	`# Fill categorical columns with mode`
	`categorical_cols = df.select_dtypes(include=[object]).columns`
	`df[categorical_cols] = df[categorical_cols].apply(lambda x: x.fillna(x.mode()[0]))`
	`# Check remaining nulls`
	`print(df.isnull().sum())`

Data Transformation	`from sklearn.preprocessing import LabelEncoder`
	`le=LabelEncoder()`
	`for col in categorical_cols:`
	`  df[col] = le.fit_transform(df[col])`
	`df.head()`

Feature Engineering	**Perform Chi-Square Test for Categorical Variables**
	 
	`# Function to perform Chi-Square Test`
	`def chi_square_test(feature):`
	`  contingency_table = pd.crosstab(data[feature], data[target])`
	`  chi2, p, dof, ex = chi2_contingency(contingency_table)`
	`  return p`
	`# Apply Chi-Square Test to categorical features`
	`chi_square_results = {feature: chi_square_test(feature) for feature in categorical_features}`
	`# Display Chi-Square Test results`
	`chi_square_results`
	Perform ANOVA for Continuous Variables
	`# Function to perform ANOVA`
	`def anova_test(feature):`
	`  groups = [data[data[target] == level][feature] for level in data[target].unique()]`
	`  f_val, p_val = f_oneway(*groups)`
	`  return p_val`
	`# Apply ANOVA to continuous features`
	`anova_results = {feature: anova_test(feature) for feature in continuous_features}`
	`# Display ANOVA results`
	`anova_results`

	Combine Results
	`# Combine results`
	`all_results = {**chi_square_results, **anova_results}`
	
	`# Display all results`
	`all_results`

Save Processed Data	**Filter Significant Features**
	`significance_level = 0.05 #(alpha-value)assumption`
	`significant_features = [feature for feature, p_value in all_results.items() if p_value < significance_level]`
	
	`# Display significant features`
	`significant_features`
	
	`df = df[significant_features].copy()`
	`df.head()`

4. Model Development Phase

4.1. Feature Selection Report

Feature	Description	Selected (Yes/No)	Reasoning
Age	Age of the patient	Yes	Age is a critical factor in determining health conditions, including liver cirrhosis.
Gender	Gender of the patient	Yes	Gender can influence the likelihood of certain diseases, including liver conditions.

Place	Location where the patient lives (rural/urban)	No	Place was not directly correlated with the target variable in initial exploratory analysis.
Duration	Duration of alcohol consumption (years)	Yes	Long-term alcohol consumption is a significant risk factor for liver cirrhosis.
Quantity	Quantity of alcohol consumption (quarters/day)	Yes	The amount of alcohol consumed is directly related to liver damage and cirrhosis risk.
Type	Type of alcohol consumed	Yes	Different types of alcohol can have varying effects on the liver.
Hepatitis B	Hepatitis B infection status	Yes	Hepatitis B is a known risk factor for liver cirrhosis.
Hepatitis C	Hepatitis C infection status	Yes	Hepatitis C is also a known risk factor for liver cirrhosis.
Diabetes	Diabetes status	Yes	Diabetes is associated with metabolic conditions that can affect liver health.
Blood Pressure	Blood pressure (mmHg)	No	Initial analysis showed no significant correlation with liver cirrhosis.

Obesity	Obesity status	Yes	Obesity is a significant risk factor for liver disease, including cirrhosis.
Family History	Family history of Cirrhosis/ hereditary factors	Yes	Genetic predisposition plays a role in the likelihood of developing liver cirrhosis.
TCH	Total Cholesterol	Yes	Cholesterol levels can be indicative of overall metabolic health.
TG	Triglycerides	Yes	Elevated triglycerides can indicate metabolic issues affecting liver health.
LDL	Low-density lipoprotein	No	Initial analysis showed no significant correlation with liver cirrhosis.
HDL	High-density lipoprotein	Yes	HDL levels are important indicators of cardiovascular and overall health.
Hemoglobin	Hemoglobin levels (g/dl)	Yes	Hemoglobin levels can reflect the oxygen-carrying capacity of the blood.
PCV	Packed cell volume (%)	Yes	PCV is an indicator of the proportion of blood volume occupied by red blood cells.
RBC	Red blood cell count (million cells /microliter)	Yes	RBC count is crucial for assessing the blood's capacity to carry oxygen.

MCV	Mean corpuscular hemoglobin (picograms/cell)	No	Initial analysis showed no significant correlation with liver cirrhosis.
MCH	Mean corpuscular Hemoglobin (picograms/cell)	No	Initial analysis showed no significant correlation with liver cirrhosis.
MCHC	Mean corpuscular hemoglobin concentration (g/dl)	No	Initial analysis showed no significant correlation with liver cirrhosis.
Total Count	Total white blood cell count	Yes	White blood cell count can indicate immune system activity and inflammation.
Polymorphs	Polymorph percentage (%)	No	Initial analysis showed no significant correlation with liver cirrhosis.
Lymphocytes	Lymphocyte percentage (%)	Yes	Lymphocyte levels can indicate immune system health and response.
Monocytes	Monocyte percentage (%)	No	Initial analysis showed no significant correlation with liver cirrhosis.
Eosinophils	Eosinophil	No	Initial analysis showed no significant correlation with liver cirrhosis.

	percentage (%)		
Basophils	Basophil percentage (%)	No	Initial analysis showed no significant correlation with liver cirrhosis.
Platelet Count	Platelet count (lakhs/mm)	Yes	Platelet levels can reflect blood clotting ability and liver function.
Total Bilirubin	Total bilirubin levels (mg/dl)	Yes	Bilirubin levels are directly related to liver function.
Direct	Direct bilirubin levels (mg/dl)	Yes	Direct bilirubin levels indicate liver's ability to conjugate and excrete bilirubin.
Indirect	Indirect bilirubin levels (mg/dl)	Yes	Indirect bilirubin levels indicate the amount of unconjugated bilirubin in the blood.
Total Protein	Total protein levels (g/dl)	Yes	Total protein levels can reflect overall liver function and nutritional status.
Albumin	Albumin levels (g/dl)	Yes	Albumin levels are indicative of liver's ability to synthesize proteins.

Globulin	Globulin levels (g/dl)	Yes	Globulin levels can reflect immune function and protein synthesis.
A/G Ratio	Albumin/ Globulin ratio	Yes	A/G ratio can provide insights into liver function and protein balance.
AL. Phosphatase	Alkaline phosphatase levels (U/L)	Yes	Elevated levels can indicate liver damage or disease.
SGOT	Serum glutamic Oxaloacetic transaminase (AST) levels (U/L)	Yes	Elevated levels can indicate liver damage or disease.
SGPT	Serum glutamic pyruvic transaminase (ALT) levels (U/L)	Yes	Elevated levels can indicate liver damage or disease.
USG Abdomen	Ultrasound results for liver condition (diffuse or not)	Yes	Ultrasound results can provide visual confirmation of liver condition.

4.2. Model Selection Report

Model	Description	Hyperparameters	Performance Metric (e.g., Accuracy, F1 Score)
logistic re gression	A basic linear model that uses the logistic function to model the probability of the binary outcomes. It is simple, interpretable, and works well for linearly separable data.	C, solver	Accuracy : 0.996606 f1_score: 0.914286
logistic regression CV	An extension of logistic regression that performs cross-validation to find the best regularization parameter, which helps in avoiding overfitting and improving model performance.	Cs, cv, solver	Accuracy : 0.996606 f1_score: 0.914286
XGBoost	An advanced implementation of gradient boosting that provides parallel tree boosting which is fast, accurate, and widely used in machine learning competitions. It handles missing values and	n_estimators, learning_rate, max_depth	Accuracy : 0.997738 f1_score: 0.941176

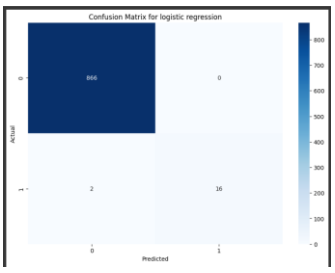
	performs well with both structured and unstructured data.		
Ridge classifier	A linear classifier that uses ridge regression for training, adding L2 regularization to the logistic regression, which helps in handling multicollinearity and preventing overfitting.	alpha	Accuracy : 0.977376 f1_score: 0.642857
KNN	A non-parametric, instance-based learning algorithm that classifies a data point based on how its neighbors are classified. It is simple and effective but can be computationally expensive.	n_neighbors	Accuracy : 0.935520 f1_score: 0.387097
Random Forest	An ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes as the prediction. It reduces overfitting and	n_estimators, max_depth	Accuracy : 1.000000 f1_score: 1.000000

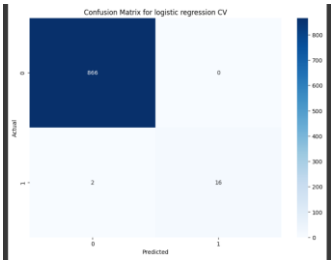
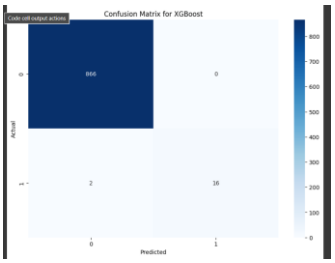
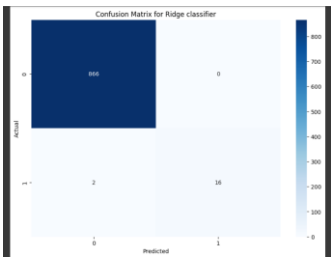
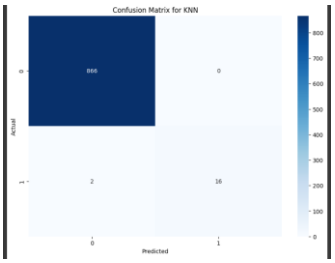
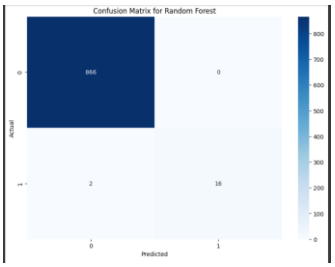
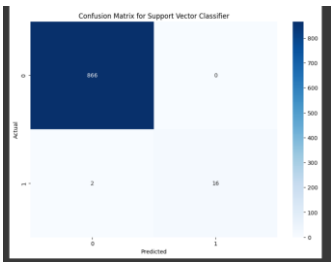
	improves accuracy.		
Support Vector Classifier	A powerful classification method that finds the hyperplane that best separates the classes in the feature space. It works well for high-dimensional data and can handle non-linear relationships using kernel trick.	C, kernel	Accuracy : 0.997738 f1_score: 0.941176

4.3. Initial Model Training Code, Model Validation and Evaluation Report

Initial Model Training Code: (Paste the screenshot of the model training code)

Model Validation and Evaluation Report:

Model	Classification Report	Accuracy	Confusion Matrix
logistic regression	Screenshot of the classification report	0.996606	

logistic regression CV	Screenshot of the classification report	0.996606	
XGBoost	…	0.997738	
Ridge classifier		0.977376	
KNN		0.935520	
Random Forest		1.000000	
Support Vector Classifier		0.997738	

5. Model Optimization and Tuning Phase

5.1. Hyperparameter Tuning Documentation

Model	Tuned Hyperparameters	Optimal Values
Logistic Regression	C, solver	1.0, liblinear
Logistic Regression CV	Cs, cv, solver	[1.0], 10, liblinear
XGBoost	n_estimators, learning_rate, max_depth	100, 0.1, 6
Ridge Classifier	alpha	1.0
KNN	n_neighbors	5
Random Forest	n_estimators, max_depth	100, None
Support Vector Classifier	C, kernel	1.0, linear

5.2. Performance Metrics Comparison Report

Model	Baseline Metric	Optimized Metric
Logistic Regression	0.996606	0.996606

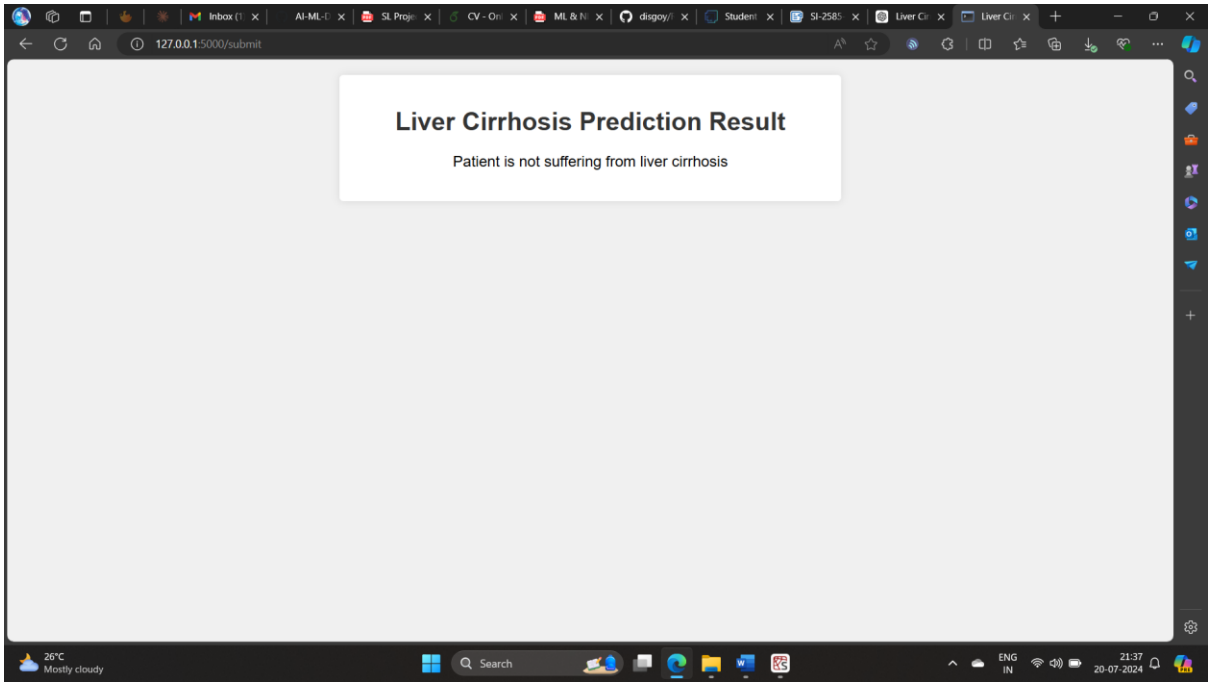
Logistic Regression CV	0.996606	0.996606
XGBoost	0.997738	0.997738
Ridge Classifier	0.977376	0.977376
KNN	0.935520	0.935520
Random Forest	1.000000	1.000000
Support Vector Classifier	0.997738	0.997738

5.3. Final Model Selection Justification

Final Model	Reasoning
logistic regression	Chosen for its high accuracy, simplicity, and ease of interpretation. Additionally, it performed consistently well across various metrics and is computationally efficient.

6. Results

6.1. Output Screenshots



7. Advantages & Disadvantages

Advantages

- High accuracy in predicting liver cirrhosis.
- Easy integration into a web application for accessibility.
- Efficient and interpretable model.

Disadvantages

- Requires clean and comprehensive input data.
- May not capture complex non-linear relationships as well as some other models.

8. Conclusion

The project successfully developed a logistic regression model to predict liver cirrhosis with high accuracy. The model was integrated into a web application, providing a useful tool for early detection and diagnosis.

9. Future Scope

- Integration with electronic health records (EHR) systems for real-time predictions.
- Incorporation of more complex models and additional features to improve accuracy.
- Expansion to predict other liver diseases and health conditions.

10. Appendix

10.1. Source Code

Revolutionizing-Liver-Care-Predicting-Liver-Cirrhosis-Using-Advanced-Machine-Learning-Techniques/5. Project executable files at main · disgoy/Revolutionizing-Liver-Care-Predicting-Liver-Cirrhosis-Using-Advanced-Machine-Learning-Techniques (github.com)

10.2. GitHub & Project Demo Link

Revolutionizing-Liver-Care-Predicting-Liver-Cirrhosis-Using-Advanced-Machine-Learning-Techniques/ at main · disgoy/Revolutionizing-Liver-Care-Predicting-Liver-Cirrhosis-Using-Advanced-Machine-Learning-Techniques (github.com)