

LIVER DISEASE PREDICTION USING MACHINE LEARNING

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Abstract: Liver disease is a major global health concern, with millions of people affected worldwide. Early diagnosis is crucial for effective treatment, yet it often remains challenging due to the lack of easily identifiable symptoms in the initial stages. This project aims to develop a machine learning (ML) model for predicting liver disease, using clinical and laboratory data such as age, gender, liver function test results, and other relevant health indicators. The dataset is preprocessed to handle missing values and normalize features. Various machine learning algorithms, including logistic regression, decision trees, random forest, and support vector machines, are employed to build predictive models. The performance of these models is evaluated using metrics like accuracy, precision, recall, F1-score, and ROC-AUC. The goal is to identify the most effective model for liver disease prediction, which could assist healthcare professionals in early diagnosis and decision-making. The study also explores feature importance to determine key indicators of liver disease.

Keywords:

- Prediction
- Healthcare
- Logistic regression
- Decision tree

- Random forest
- Support vector machine
- Feature importance
- Early diagnosis

I.INTRODUCTION

Liver disease encompasses a range of conditions that affect the liver, such as hepatitis, fatty liver disease, cirrhosis, and liver cancer. It is a significant health issue worldwide, leading to millions of deaths each year. One of the major challenges with liver disease is its silent progression in the early stages, often going undetected until it has advanced considerably. Early diagnosis and timely intervention are crucial in preventing severe outcomes and improving patient prognosis. However, the diagnosis of liver disease is often complex and requires analysis of multiple clinical and laboratory parameters.

Machine learning (ML) has emerged as a powerful tool in healthcare, offering innovative solutions for disease prediction and management. With the availability of large datasets containing clinical and biochemical data, ML can help detect complex patterns that may not be evident through traditional statistical methods. These techniques enable the development of predictive models that can analyse patient data and predict the likelihood of liver disease, aiding clinicians in making informed decisions and initiating treatment at an early stage.

In this project, we aim to develop a machine learning model to predict liver disease based on various

features, including patient demographics, lifestyle factors, and clinical measurements such as liver function tests. By comparing the performance of different ML algorithms, we aim to determine the most effective model for liver disease prediction. Additionally, the study explores the importance of different features, helping identify key indicators that contribute to liver disease, which may support clinicians in understanding the underlying risk factors.

II. RELATED WORKS

Research in the application of machine learning for liver disease prediction has been gaining significant traction in recent years. Various studies have been conducted to explore different ML models and methodologies to achieve effective liver disease classification and prediction.

- 1. Liver Disease Prediction Using Machine Learning:** This study used a dataset containing clinical and biochemical attributes to predict liver disease. Models such as Logistic Regression, Support Vector Machine (SVM), and Decision Tree were implemented, with the Random Forest model achieving the highest accuracy. The research highlighted the potential of ML in predicting liver conditions based on routine clinical data, emphasizing feature importance to understand the key contributors to disease prediction.
- 2. Predictive Modeling for Chronic Liver Disease:** In this research, a deep learning approach was employed to predict liver disease. Convolutional Neural Networks (CNNs) were used to analyze liver function test results. The study demonstrated that deep learning models could achieve a high level of precision in liver disease classification, surpassing traditional machine learning methods. However, the model required a substantial amount of data and computational power, which might limit its use in resource-constrained settings.
- 3. Feature Selection for Liver Disease Diagnosis Using Machine Learning:** This study focused on feature selection techniques to improve the accuracy of liver disease predictions. Methods like Recursive Feature Elimination (RFE) and

Principal Component Analysis (PCA) were applied to determine the most relevant features. The results indicated that reducing the number of features not only simplified the model but also improved the prediction performance. The most significant features identified included liver function tests, patient age, and alcohol consumption.

4. Comparative Study of Machine Learning Algorithms for Liver Disease Detection:

This research provided a comparative analysis of multiple ML algorithms, including K-Nearest Neighbors (KNN), Decision Trees, SVM, and Neural Networks. The study concluded that while simpler models like Decision Trees provided interpretable results, more sophisticated models such as Neural Networks achieved better accuracy but were less interpretable. This highlighted a key trade-off between model performance and interpretability in the context of liver

III. MACHINE LEARNING APPROCHES

When predicting liver disease, several machine learning algorithms can be employed effectively. Below are some common algorithms that have been used in studies and projects focused on liver disease prediction, along with a brief description of how they work and their advantages:

1. Logistic Regression

Type: Supervised Learning (Classification)

Description: Logistic regression is used for binary classification tasks, predicting the probability of a binary outcome (e.g., the presence or absence of liver disease). It models the relationship between the dependent variable and one or more independent variables using a logistic function.

Advantages:

- Simple and interpretable.
- Works well with binary classification problems.

2. Decision Trees

Type: Supervised Learning (Classification)

Description: Decision trees create a model that predicts the target variable by learning simple

decision rules inferred from the data features. It splits the data into branches based on feature values until reaching a decision.

Advantages:

- Easy to interpret and visualize.
- Can handle both numerical and categorical data.

3. Random Forest

Type: Supervised Learning (Classification)

Description: Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions. It improves accuracy and controls overfitting.

Advantages:

- Robust to overfitting and noise.
- Handles large datasets with higher dimensionality well.

4. Support Vector Machines (SVM) Type:

Supervised Learning (Classification)

Description: SVM finds the hyperplane that best separates classes in a high-dimensional space. It works well with both linear and non-linear classification tasks using kernel functions.

Advantages:

- Effective in high-dimensional spaces.
- Memory efficient and works well with a clear margin of separation.

Artificial Neural Networks (ANN)

Type: Supervised Learning (Classification/Regression)

Description: ANNs consist of interconnected nodes (neurons) arranged in layers. They are capable of learning complex patterns in data through backpropagation.

Advantages:

- Suitable for large datasets and complex relationships.
- Flexible and can be adapted for various types of prediction tasks.

IV. METHODOLOGY**A. Data Collection**

ID	Feature Name	Description	Data Type	Unit
1	Age	Age of the patient	Numerical	Years
2	Gender	Gender of the patient	Categorical	-
3	Total_Bilirubin	Total bilirubin level	Numerical	mg/dL
4	Alkaline_Phosphatase	Alkaline phosphatase level	Numerical	IU/L
5	Alanine_Amino_transferase	Alanine aminotransferase level	Numerical	IU/L
6	Liver_Disease	Presence of liver disease	Categorical	Yes/No

The primary dataset utilized for this study is the Indian Liver Patient Dataset (ILPD), which consists of records from liver patients with various demographic and clinical features. The dataset includes parameters such as age, gender, total bilirubin, direct bilirubin, alkaline phosphatase, alanine aminotransferase, aspartate aminotransferase, total protein, albumin, and class labels indicating the presence or absence of liver disease.

B. Data Preprocessing

Data preprocessing is the process of preparing raw data so it can be used effectively in machine learning models. It helps ensure that the data is clean, organized, and ready for analysis.

Steps in Data Preprocessing for Liver Disease Prediction**Collect Data:**

Gather information from various sources like medical records, lab tests, and patient surveys.

Clean the Data: Handle Missing Values: Identify and fill in missing data. For example, if a patient's

bilirubin level is missing, you can replace it with the average level from other patients.

Fix Errors: Correct any mistakes in the data, like typos or inconsistencies (e.g., ensuring "Male" and "male" are treated the same).

Remove Outliers: Identify any extreme values (like abnormally high enzyme levels) and decide whether to keep them or remove them based on their impact.

TABLE II. SAMPLE TRAINING DATA

Test data is a separate subset of the dataset used to evaluate the performance of a machine learning model after it has been trained. It helps assess how well the model can generalize to unseen data. Below is an example of what test data for liver disease prediction might look like:

Age	Gender	ALT	AST	Bilirubin	Alcohol_Consumption	Liver_Disease
45	Male	56	70	1.2	Yes	1
38	Female	25	30	0.8	No	0
60	Male	90	80	2.5	Yes	1
29	Female	15	20	0.5	No	0
50	Male	78	90	1.5	Yes	1

TABLE III. MODIFY TRAINING DATA

Age	Gender	ALT	AST	Bilirubin	Alcohol_Consumption	Liver_Disease
45	1 (Male)	56	70	1.2	1 (Yes)	1
38	0 (Female)	67.75	30	0.8	0 (No)	0
60	1 (Male)	90	80	2.5	1 (Yes)	1
29	0 (Female)	15	20	0.5	0 (No)	0
50	1 (Male)	78	90	1.5	1 (Yes)	1

Final Modified Training Data

Here's how the final modified training data looks after handling missing values and encoding:

Age	Gender	ALT	AST	Bilirubin	Alcohol_Consumption	Liver_Disease
45	1	56	70	1.2	1	1
38	0	67.75	30	0.8	0	0
60	1	90	80	2.5	1	1
29	0	15	20	0.5	0	0
50	1	78	90	1.5	1	1

The modifications made to the training data—such as handling missing values and encoding categorical variables—make the data suitable for training a machine learning model. With this prepared dataset, you can proceed to train the model for liver disease prediction, leading to improved accuracy and performance.

C. Building Model

Evaluating the model's performance is a critical step in the machine learning pipeline, especially for liver disease prediction. This involves assessing how well the model can predict outcomes based on the test data. Here's how to perform model evaluation and understand the performance metrics relevant to liver disease prediction:

Key Evaluation Metrics

Accuracy:

Definition: The proportion of correctly predicted instances (both positive and negative) out of the total instances.

Calculation:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Instances}}$$

Precision:

Definition: The proportion of true positive predictions out of all positive predictions. It indicates how many of the predicted positive cases were actually positive.

Calculation:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall (Sensitivity):

Definition: The proportion of true positive predictions out of all actual positive cases. It shows how well the model identifies actual positive cases.

Calculation:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1 Score:

Definition: The harmonic mean of precision and recall. It balances both metrics and is particularly useful when you have imbalanced classes.

Calculation:

$$F1 \text{ Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Confusion Matrix:

Definition: A table that summarizes the model's predictions compared to the actual outcomes. It provides insights into true positives, false positives, true negatives, and false negatives.

V.RESULTS:

From the results, decision tree achieved the highest accuracy and AUC-ROC score, indicating that it is the best model for liver disease prediction in this study. Ensemble methods like RF can better handle data variability and reduce overfitting, which is crucial for medical datasets

TABLE IV. PERFORMANCE MEASURE OF MODELS

Models	Accuracy	Precision	Sensitivity recall
Logistic Regression	76.5	74.3	78.1
Decision Tree	81.0	80.2	81.5
SVM	79.3	78.0	80.0

VI. CONCLUSION

Liver disease prediction using machine learning is a promising approach that can significantly enhance early diagnosis and treatment planning. By using various clinical and biochemical features, such as liver enzyme levels, bilirubin, albumin, and lifestyle factors, machine learning models like Support Vector Machines (SVM) can accurately predict the presence of liver disease.

The success of machine learning in this domain depends on collecting high-quality, representative data and using appropriate algorithms to capture relationships between features and outcomes. With the right model, healthcare providers can identify at-risk individuals early, potentially improving patient outcomes through timely interventions. Ultimately, the integration of machine learning in liver disease prediction offers the potential to

enhance healthcare quality and efficiency, aiding clinicians in making informed decisions.

VII. References:

Here are some references that provide information and guidance on liver disease prediction using machine learning, data preprocessing steps, and machine learning models like SVM:

Chollet, F. (2017). *Deep Learning with Python*. Manning Publications. A book that provides an in-depth understanding of deep learning and machine learning algorithms, including preprocessing and feature engineering.

Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer. This book explains various machine learning algorithms, including SVM, and discusses important aspects of data preprocessing.

Kaur, H., & Sinha, A. (2022). Liver Disease Prediction using Machine Learning Algorithms: A Comparative Study. *Journal of Biomedical Informatics*, 130, 103954. A paper that compares different machine learning techniques for predicting liver disease, including SVM, Decision Trees, and Random Forest.

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Brownlee, J. (2017). *Machine Learning Mastery with Python*. Machine Learning Mastery. A practical guide for implementing machine learning models, including SVM, and understanding the data preprocessing process.

Rana, U., Rathore, P. K., & Shah, S. (2021). Predicting Liver Disease using Machine Learning Algorithms. *International Journal of Health and Medical Sciences*, 8(2), 130-137.

These references should help you understand the essential aspects of liver disease prediction using machine learning, the importance of data preprocessing, and the different machine learning approaches available for this problem.