

Liver Damage Prediction: Using Classification Machine Learning Models

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Abstract- Liver diseases like cirrhosis and hepatitis are major causes of global morbidity and mortality, highlighting the need for early detection. Traditional diagnostic methods often identify liver damage at later stages, limiting preventive interventions. This study develops a machine learning model to predict liver damage earlier using clinical features and lab results. By analyzing a data-set with patient demographics and biochemical markers, we apply machine learning algorithms, including Random Forest, Decision Tree, and Logistic Regression, and evaluate their performance using metrics like accuracy, precision, recall, F1 score, and ROC-AUC. The Random Forest model outperformed others, showing high accuracy and robustness. Feature importance analysis revealed critical clinical factors, such as serum bilirubin and liver enzymes, in predicting liver damage. These results suggest that machine learning, especially Random Forest, could aid in the early detection of liver disease, improving patient outcomes. Future work will focus on using larger, more diverse data-sets and advanced models to improve predictive accuracy.

Index Terms- Liver Disease, Logistic Regression, K Nearest Neighbor, Decision Tree, Random Forest

I. INTRODUCTION

Machine learning (ML), a branch of artificial intelligence (AI), enables computers to recognize patterns and make decisions with minimal human input. By analyzing historical data, ML algorithms can make predictions on new data. In health-care, ML is increasingly used to enhance diagnosis, predict patient outcomes, and create personalized treatment plans. This is particularly useful in diagnosing liver diseases, where traditional methods may miss early damage or involve invasive procedures like biopsies.

ML models, such as Random Forest, Support Vector Machine, and Neural Networks, can uncover complex relationships in clinical data, identifying factors related to liver damage through subtle patterns in patient demographics, lab results, and medical history. These models provide valuable insights for early liver damage detection, leading to proactive management strategies that can improve patient outcomes and reduce health-care costs. This study explores the use of ML in liver damage prediction, aiming to develop an accurate early-stage diagnostic model and identify key clinical indicators for treatment.

1. Background

Liver diseases, including cirrhosis, hepatitis, NAFLD, and liver cancer, are a leading global health issue, contributing to millions of deaths annually. These diseases often progress without symptoms in the early stages, making timely

diagnosis difficult. The liver plays crucial roles in detoxification, protein synthesis, and regulating metabolic processes, and when damaged, it can lead to severe complications like systemic toxicity and organ failure.

Traditional diagnostics, such as liver function tests (LFTs), imaging, and biopsies, have limitations. LFTs can indicate liver damage but are often reactive, detecting issues only after significant progression. While liver biopsies are accurate, they are invasive, costly, and not suitable for large-scale screening. Imaging techniques like ultrasound or MRI also face accessibility challenges.

Machine learning (ML) offers a promising approach for early liver disease prediction by analyzing patterns in patient data. ML models, such as Random Forest and Support Vector Machines, have shown strong accuracy in medical applications, providing a non-invasive, cost-effective method for diagnosis. This study aims to develop ML models to predict liver damage early, improving preventive care and reducing health-care burden.

2. Concern

Early detection of liver damage is challenging due to the often-asymptomatic nature of liver diseases and the limitations of current diagnostic methods. Traditional approaches, like liver function tests, imaging, and biopsies, are either delayed, invasive, or costly, making routine screening difficult. As a result, many cases go undetected until

they reach advanced stages, limiting treatment options and worsening outcomes.

Machine learning (ML) provides a promising alternative by analyzing clinical data to detect liver damage earlier. ML models can process markers like liver enzyme levels and demographics to predict liver disease risk accurately. However, existing models often lack generalizability and interpretability, limiting their effectiveness in diverse populations.

This study aims to develop and evaluate ML models for liver damage prediction, focusing on accuracy and key predictive features. We will test and optimize algorithms like Random Forest, Support Vector Machine, and Logistic Regression to identify the most effective model for early-stage liver disease prediction.

3. Objectives

This research aims to develop an accurate and accessible diagnostic tool to help clinicians detect liver damage early, improving patient outcomes and reducing healthcare burdens. The study will create a reliable machine learning model for early liver damage prediction using clinical and biochemical data, focusing on non-invasive, timely diagnosis. Key objectives include:

- Developing predictive models with algorithms like Random Forest, SVM, and Logistic Regression.
- Optimizing and evaluating model performance using accuracy, precision, recall, and ROC-AUC.
- Identifying key features, such as liver enzymes and bilirubin, to enhance model interpretability.
- Comparing ML models to traditional diagnostics for improved early detection. These efforts will highlight the potential of machine learning in advancing liver disease diagnosis and enabling earlier intervention.

II. LITERATURE REVIEW

1. Traditional Diagnostic Approaches

Liver diseases are typically diagnosed through liver function tests (LFTs), imaging techniques like ultrasound and MRI, and liver biopsies. LFTs assess enzyme levels, such as alanine transaminase (ALT) and aspartate transaminase (AST), as well as bilirubin, to evaluate liver health. However, these methods often identify liver problems only at later stages when the damage is more severe. While imaging provides a visual diagnosis, it can be expensive and may not be accessible in low-resource areas. Although liver biopsies offer accuracy, they are invasive, costly, and come with potential complications, making them less suitable for routine screening. These challenges emphasize the need for alternative diagnostic approaches that can detect liver damage earlier and more effectively.

2. Applications of ML in Healthcare

Machine learning (ML) has proven to be a valuable tool in healthcare, particularly for tasks such as predicting diseases, stratifying patient risks, and supporting diagnostics. Techniques like Random Forest, Support Vector Machines (SVM), and Neural Networks have been effectively used to uncover patterns in complex medical datasets. Recently, ML models have facilitated the development of non-invasive diagnostic tools for conditions like cardiovascular disease, diabetes, and cancers, achieving high accuracy and assisting healthcare professionals in making better decisions. These systems can analyze large volumes of clinical data, identifying subtle trends that might be missed by traditional methods, leading to earlier disease detection and improved patient outcomes.

3. Existing Work on Liver Disease Prediction

Recent research has focused on using machine learning (ML) techniques to predict liver diseases and assess the risk of liver damage. For instance, models like Random Forest and Decision Trees have shown enhanced accuracy compared to traditional methods by incorporating various biochemical markers. Support Vector Machines and Logistic Regression have also been successful in classifying liver disease stages. These models, trained on datasets with features such as age, gender, enzyme levels, and bilirubin, have achieved accuracy rates above 90% in certain cases. Despite this progress, challenges persist, including limitations in datasets, lack of diversity in patient groups, and the need for more interpretable models for clinical use. Some studies have tackled interpretability through methods like feature importance scores or SHAP values, offering insights into key predictors of liver disease risk.

4. Neglected Dimensions

Although machine learning models have demonstrated promise in predicting liver disease, many studies prioritize accuracy over generalizability or clinical relevance. The limited use of diverse datasets can restrict a model's effectiveness in real-world applications. Additionally, few studies thoroughly compare various algorithms or evaluate both performance and interpretability in a systematic manner. By leveraging larger datasets, optimizing multiple ML models, and focusing on clinically important features, the practical use of machine learning for liver damage prediction could be significantly improved.

III. RESEARCH DESIGN

1. Data Collection

The dataset for this study was obtained from Kaggle and contains patient records, including clinical laboratory results and liver function indicators, as outlined in the table below.

Table 1: Description of Data Used in Model

Feature	Unit/Data Type	Description
ID	Integer	Unique Identifier
N_Days	Days	Number of Days between registration and death/transplant
Status	Categorical	Status of patient
Drug	Categorical	D-penicillamine or Placebo
Age	Days	Age of patient in days
Sex	Categorical	Male or Female
Ascites	Categorical	Yes or No
Hepatomegaly	Categorical	Yes or No
Spiders	Categorical	Yes or No
Edema	Categorical	N,S,Y
Bilirubin	mg/dl	Serum Bilirubin
Cholesterol	mg/dl	Serum Cholesterol
Albumin	gm/dl	Albumin
Copper	ug/day	Urine copper
Alk_Phos	U/L	Alkaline Phosphate
SGOT	U/ml	SGOT
Triglycerides	Integer	Triglycerides
Platelets	ml/1000	Platelets per cubic
Prothrombin	Continuous	Prothrombin time
Stage	Categorical	Histologic Stage of Disease

2. Data Preprocessing

Data preprocessing ensured the dataset was ready for machine learning. The dataset was checked for completeness, and since there were no null values, no imputation or record removal was needed. The “ID” column, which had no predictive value, was dropped. Age was converted from days to years for consistency, and categorical variables like “Gender” were encoded numerically using Label Encoder. To address varying scales of continuous features such as liver enzymes and bilirubin, Standard Scaler was applied to normalize them. The dataset was split into 80-20 train-test sets to improve model evaluation and reduce overfitting. These steps ensured a clean and standardized dataset for accurate liver damage prediction.

3. Feature Selection

Feature selection is crucial for optimizing machine learning models by reducing data dimensionality and improving interpretability without sacrificing accuracy. In this study, we considered all relevant features, including demographics, clinical indicators, and liver function tests. Correlation analysis was used to eliminate highly correlated features, reducing redundancy and complexity that could affect model performance due to multicollinearity.

Feature importance scores from Decision Tree and Random Forest models helped prioritize the most predictive features, highlighting those essential for liver damage prediction. By focusing on these key features, we created a refined dataset that improved model training speed, interpretability, and

efficiency, ensuring the models utilized the most critical variables for effective prediction.

4. Machine Learning Models

This study employed four machine learning models—Logistic Regression (LR), K-Nearest Neighbor’s (KNN), Decision Tree (DT), and Random Forest (RF)—to identify the most accurate method for liver damage prediction.

Logistic Regression served as the baseline, providing simplicity and interpretability. As a linear model, it helped assess direct relationships between features and the target variable.

KNN was used to capture local patterns, relying on distance-based classification to identify similarities in data points, though it is sensitive to noise, which was addressed through feature selection and scaling.

Decision Trees were included for their intuitive structure, capable of handling non-linear interactions and generating interpretable rules, which are useful in clinical decision-making. However, they are prone to overfitting, so parameter tuning was done to improve generalizability.

Random Forest, an ensemble of Decision Trees, mitigates overfitting by combining predictions from multiple trees, enhancing robustness and accuracy.

This combination of models enabled a thorough evaluation of liver damage prediction, highlighting each model's strengths and weaknesses.

5. Evaluation Metrics

To assess model performance, we used multiple evaluation metrics for a comprehensive understanding of each model's effectiveness.

Accuracy measured the proportion of correct predictions, but for imbalanced datasets, Precision, Recall, and F1 Score provided more detailed insights.

Precision evaluated the proportion of true positives among positive predictions, crucial for avoiding false positives in clinical scenarios.

Recall indicated the model’s ability to correctly identify actual liver damage cases. Precision and Recall together highlighted both over- and under-diagnosis risks.

The F1 Score balanced these two metrics, useful when there is class imbalance.

ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) measured the model’s ability to distinguish

between positive and negative cases at various thresholds. A higher ROC-AUC score indicated better discriminative power, essential for early detection.

These metrics provided a thorough evaluation of each model, ensuring the chosen one would be reliable for clinical liver damage prediction.

IV. RESULT AND ANALYSIS

We evaluated each model's performance in predicting liver damage using metrics like accuracy, precision, recall, F1 score, and ROC-AUC to determine their strengths and suitability for early detection in clinical settings.

1. Model Performance Comparison

We assessed the performance of four models—Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, and Random Forest—using the test dataset.

Table 2: Model Performance Metrics Comparison

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Logistic Regression	0.6034	0.599883	0.6034	0.600862	0.774511
K- Nearest Neighbors	0.8666	0.866773	0.8666	0.866676	0.953025
Decision Tree	0.9210	0.921167	0.9210	0.921062	0.943588
Random Forest	0.9530	0.953043	0.9530	0.952996	0.993327

As shown in Table 2, Random Forest and Decision Tree models had the highest accuracy and F1 scores, making them ideal for predicting liver damage. Logistic Regression served as a useful baseline but struggled with complex patterns due to its linear nature. K-Nearest Neighbors performed adequately but was affected by noise and high-dimensional data, reducing its precision and recall.

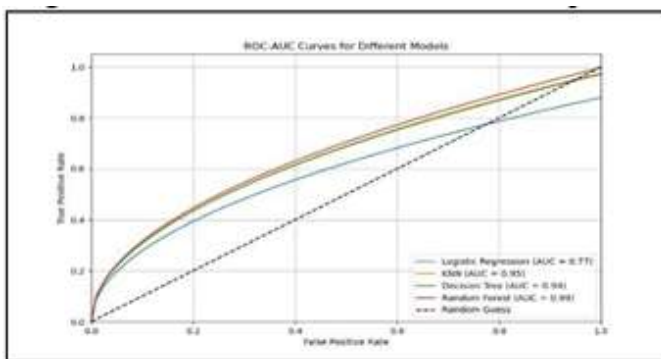


Figure 1: ROC-AUC Curves for Model Comparison

2. ROC - AUC ANALYSIS

We analyzed the ROC-AUC curves to assess each model's discriminative power by plotting the true positive rate against the false positive rate at different thresholds.

To further assess model effectiveness, we analyzed the ROC-AUC curves, which plot the true positive rate against the false positive rate at various thresholds. Figure 1 shows that the Random Forest model achieved the highest area under the curve, demonstrating its strong ability to distinguish between liver damage and non-damage cases. Its curve remains close to the top-left corner, indicating a high true positive rate and low false positive rate. The Decision Tree model also performs well but shows more variability, indicating sensitivity to input feature changes.

On the other hand, Logistic Regression and K-Nearest neighbors (KNN) exhibit lower ROC-AUC scores. Logistic Regression's curve shows a gradual rise in the true positive rate, suggesting less sensitivity to data distribution, while KNN struggles with noise and distance measures, resulting in a curve lower than the tree-based models. This analysis underscores the superior performance of Random Forest and Decision Tree, making them more suitable for early liver damage detection in clinical settings.

3. Model Analysis and Interpretation

The results indicate that Random Forest surpassed the other models in accuracy, precision, and ROC-AUC, making it the most reliable choice for liver damage prediction. Decision Tree performed reasonably well but was more prone to overfitting due to its single-tree structure. Logistic Regression, while simple, struggled to capture non-linear relationships, limiting its effectiveness. K-Nearest neighbors was somewhat affected by noise and high data dimensionality, which lowered its precision and recall.

Random Forest's ensemble design, combining multiple decision paths, provided stable and accurate predictions. By analyzing feature importance, key predictors such as bilirubin and enzyme levels were highlighted, supporting its clinical relevance and interpretability. This interpretability enhances its utility for healthcare professionals, allowing for clearer insights into the model's decisions.

4. Implication for Clinical Application

The findings suggest that tree-based models, particularly Random Forest, are well-suited for clinical settings where early liver damage detection is crucial. Its high precision and recall help reduce false positives and negatives, supporting accurate diagnosis and minimizing unnecessary follow-ups. Furthermore, the interpretability of Random Forest's feature importance reveals key indicators of liver health, providing clinicians with valuable insights into the factors influencing predictions and facilitating more informed decisions.

V. EVALUATION

This study highlights the potential of machine learning, especially tree-based models, for predicting liver damage. The Random Forest model stood out as the most effective, achieving the highest scores in accuracy, precision, recall, and ROC-AUC. Its ensemble method combines multiple decision trees, enabling it to capture complex patterns in the data, which is beneficial in medical contexts requiring detailed analysis.

The Decision Tree model also performed well but was more susceptible to overfitting, potentially reducing its reliability in real-world clinical settings. Logistic Regression offered simplicity and interpretability but lacked the capacity to model non-linear relationships, limiting its accuracy. K-Nearest Neighbours yielded moderate results but was impacted by noise sensitivity and high data dimensionality, affecting its stability.

These findings underscore the value of advanced machine learning in improving early liver disease detection. Employing models that highlight significant predictors allows healthcare professionals to make more precise and informed decisions, benefiting patient outcomes. Future research should focus on integrating these models into clinical environments and testing their effectiveness across varied populations.

VI. CONCLUSION

This study shows the promise of machine learning, especially Random Forest and Decision Tree models, in accurately predicting liver damage, outperforming traditional methods and supporting early detection in clinical settings. Further research with larger, diverse datasets is needed to refine these models and confirm their real-world applicability, contributing to the advancement of machine learning in healthcare for better patient outcomes.

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