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Enhancing Liver Disease Detection and Management with Advanced Machine Learning Models

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Abstract: The prevalence of hearing loss has risen making it a significant public health issue. Hearing loss is caused by complicated pathophysiological pathways, with various risk factors identified, such as hereditary factors, inflammatory processes, systemic disorders, noise exposure, medicines, oxidative stress, and age. Metabolic syndrome is a medical condition characterized by the presence of hypertension, central obesity, hyperlipidemia, and diabetes. Metabolic syndrome has been linked to several clinical diseases, such as stroke, heart attack, cardiovascular disease-related death, and diabetes. A cross-sectional study was done on 100 patients with metabolic syndrome which used specific cut-off points of waist circumference, fasting glucose levels, blood pressure, triglyceride, and high-density lipoprotein cholesterol levels to diagnose the condition. Among these five criteria, at least three had to be met, and the presence of additional criteria indicated greater severity. Audiological evaluation with pure tone audiometry was done and recorded. Statistical analysis was performed to determine the significance of the results. The majority of the patients (62%) had unilateral hearing loss, amongst which sensory-neural type and moderately severe hearing loss were the most common type (67%) and severity (61%) of hearing loss respectively. Chi-square tests were done for the comparison of type, severity, and laterality of hearing loss with age, gender of the patients, and criteria fulfilled for metabolic syndrome. The severity of hearing loss had a statistically significant association with the age of the patients and the number of criteria fulfilled for metabolic syndrome with a p-value of 0.003. There was a statistically significant association between the severity of hearing loss and the age of the patients and the number of criteria fulfilled for metabolic syndrome with a p-value of 0.004. Metabolic syndrome affects the auditory system in several ways. It damages hearing and exacerbates presbycusis. Hearing loss worsens as components of the metabolic syndrome increase.

Introduction

Liver disease is a huge problem in global health since it affects millions of individuals worldwide. The effective treatment of liver illness and the avoidance of harmful health effects depend on a prompt and accurate diagnosis, according to Salam et al. (2023). The conventional approaches, such as physical examinations, laboratory testing, and imaging investigations, are not always accurate or quick. Recently, ML techniques have shown promise as a tool to improve the accuracy of liver disease

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predictions, offering a potential alternative to standard diagnostic procedures that is both faster and more accurate. Computerized algorithms trained with these ML approaches can sift through massive datasets, empowering doctors to make more informed choices. Applying ML to the pressing need for better methods of predicting liver disease will improve patient care and outcomes (Najjar, 2023; Kumari et al., 2023).

Maintaining good health requires attention to the liver because it is the most vital organ in the body. The problem is that it is often disregarded while discussing medical care. Most people's poor lifestyle choices lead to liver disorders, which can range from mild to severe (Ni et al., 2022).

An experiment conducted by Keerthana et al. (2023) showed that machine learning algorithms have demonstrated good outcomes when used for predicting and detecting liver sickness. Through the utilization of modern technology's processing capacity, these algorithms comb through enormous and intricate datasets, which often contain clinical, genetic, and imaging data. Because ML models can see subtle patterns, non-linear correlations, and hidden insights in this data better than traditional methods, diagnostic accuracy has been improved (Rao et al., 2023; Rao et al., 2023; Wani et al., 2024). Additionally, they may refine and advance their predictions as they acquire additional knowledge from new data. Our objective is to develop durable and beneficial models for medical professionals. To achieve this, we will implement machine learning. Our objective is to innovate patient care and liver disease management by implementing more precise and efficient disease forecasting techniques. By addressing methods, databases, challenges, and prospective ML applications in the context of liver disease prediction, we can improve healthcare outcomes and expand our understanding of this intricate medical issue.

Literature Survey

Kuzhippallil et al. (2020) studied the use of machine learning to automatically diagnose diseases, with a focus on the increased prevalence of liver problems. The new classifier improves XGBoost by utilizing a genetic approach. Feature selection is stressed as the study examines liver disease classification algorithms and visualisation methods. An isolation forest method eliminates extreme values via outlier identification. The feature selection approach improves classification accuracy, classification time, and illness prediction efficiency.

Humans need the liver to produce bile, metabolise proteins and carbs, activate enzymes and store glycogen, vitamins and minerals (Kalaiselvi et al., 2021; Paul and Sadhukhan, 2023). Alcohol, medication, and food can cause liver illnesses, which are detected using time-consuming and expensive liver function tests and scans. Data mining methods can speed up diagnosis and improve accuracy by using large data sets. In order to alleviate the limitations of local storage, healthcare facilities employ the cloud to store their extensive data sets. Physicians use different data mining algorithms, such as KNN, Decision Tree and Adaptive Neuro-Fuzzy Inference System, to develop decision support models that support the diagnosis of liver diseases.

Singh et al. (2020) focused on the importance of readily available healthcare use software engineering methods like feature selection and classification to predict the occurrence of liver illness. In order to identify the possible occurrence of liver illness, researchers used the Indian Liver Patient Dataset housed at UC Irvine. Age, bilirubin levels, gender, and liver enzymes were among the factors taken into account. The dataset's validity is evaluated using classification methods like Naive Bayes, Random Forest, J48, and k-nearest neighbor. We tested these methods through their paces in a feature selection and non-feature selection scenario. This study also shows the potential for developing sophisticated algorithms that can predict the onset of liver disease. We developed the algorithm using software engineering methodologies to improve forecast accuracy and speed.

Amin et al. (2023) conducted research on the application of machine learning in diagnosing liver illness, emphasized the significance of the liver's functions and the urgency for prompt intervention. We used an exhaustive technique to retrieve 583 patient records from the Indian Liver Patient Dataset at UC Irvine. It studies using many different machine learning techniques, such as logistic regression, random forests, and SVMs. The suggested ML approach for liver disease classification outperforms state-of-the-art algorithms by a wide margin (88.68% F1, 92.30% recall, and 88.10% accuracy). The results show that this method might help doctors diagnose liver diseases more accurately in clinical settings.

Rao et al. (2022) studied how AI can greatly improve healthcare applications. They aimed to develop an advanced healthcare system that would use the advantages of cloud computing and artificial intelligence. Implementing AI into health data analysis and acquisition provides the possibility to improve disease detection and identification accuracy while significantly minimizing response times. Yavanamandha et al. (2023)

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demonstrated the potential use of neural networks to track an individual's activities and important signs via wireless connections and in-body sensors. These sensors may not only detect environmental factors as well as people's real-time activities. The present research looked at the use of computation as well as data analysis for healthcare and the possible benefits of AI. Enhancing healthcare prediction systems is a significant goal. These improvements show the potential to open the way for innovative ways to recognize biological faults, which would upgrade the healthcare system as an entire field.

By applying machine learning techniques, Gupta et al. (2022) analyzed and found patterns in huge databases containing information about people with liver illnesses. Their technique used supervised learning with data taken from the UCI Repository. The effective use of data from previous medical tests needs improvement if prediction is to enhance patient outcomes. Machine learning has been shown to be useful in improving the prediction capacities of healthcare systems, particularly in the diagnosis and management of liver disease. Feature selection helped the algorithms reach rather high degrees of accuracy.

An algorithm for predicting fatty liver disease was created by Islam et al. (2018) using a dataset with 994 individuals. The logistic regression model outperformed the others, achieving a sensitivity of 74.10%, specificity of 64.90%, and accuracy of 76.30%. This model can enhance clinical decision-making through the use of electronic medical data. It is especially effective in predicting fatty liver disease.

Dritsa and Śriga (2023) did a study examining how machine learning methods can be used to find early liver disease. The study was mainly about how important the liver is for breaking down nutrients and getting rid of waste. Many tests are done on the Voting classifier and other machine learning models and ensemble methods to see how well they work. After SMOTE and 10-fold cross-validation made some changes, the Voting classifier did a great job. Its recall, accuracy, precision, F-measure, and area under the curve (AUC) values were 80.1%, 80.4%, 80.1%, and 88.4%, respectively. With this information, it's clear that ML could make diagnosing and treating liver disease easier and faster.

Aswini et al. (2023) introduce a modified Mask-regional convolutional neural network architecture that is supplemented with the Pelican Optimisation Algorithm (POA) for the early prediction of liver disorders. The datasets used in this study include those of Indian liver patients, hepatitis C, and cirrhosis. This approach is aimed at reducing the complexity and cost of current predictive methods. The POA helps balance training losses in the model, which extracts and analyzes liver disease features to identify diagnostic correlations. The performance of this model is compared with other advanced methods. The proposed work showcases its potential for early disease detection and easing the burden on physicians.

Mostafa et al. (2021) examine the application of machine learning algorithms to improve the diagnosis of liver disease in a sample of 615 patients. Utilizing artificial intelligence alongside traditional methods, the research involved handling missing data through multiple imputations by chained equations and reducing dimensionality with principal component analysis. The effectiveness of various binary classifier algorithms was compared, with RF demonstrating superior accuracy at 98.14%. This approach not only addresses issues of overfitting via the synthetic minority oversampling technique but also confirms the potential of ML to enhance diagnostic accuracy and patient care by incorporating clinical data with advanced analytics.

Methodology

In the proposed model, as shown in Figure 1, the hepatitis dataset is considered (Sachdeva et al., 2023). This dataset is pre-processed in which null values are filled and all values are converted into numbers, i.e., categorical to an integer, because training and testing can be done only on integer values.

Various models, such as SVM, Random Forest Classifier, Decision Tree Classifier, and Ensemble method (XGBoost, AdaBoost), are used to train the trained data (Sekhar et al., 2021; Srinivasa Rao et al., 2023). The trained data is modelled and classification is done, i.e., Patient with disease and patient with no disease. Then, the stage if disease is determined for each patient. After the prediction is done, performance metrics are calculated for each model.

Dataset and Preprocessing

The dataset contains the features Age, Sex, ALT, ALP, ALB, AST, BIL, CHOL, CHE, GGT, CREA, PROT and Category, which gives the condition of the patient. The dataset contains information about 615 patients. Initially, the dataset consists of null values. These null values are pre-processed and filled with mean values of the corresponding feature values. After filling, the null value count is 0 for all features.

Null Values Handling

Initially, the dataset contains null or missing values. Proper handling of null data is necessary since they can impair the performance of machine learning models.

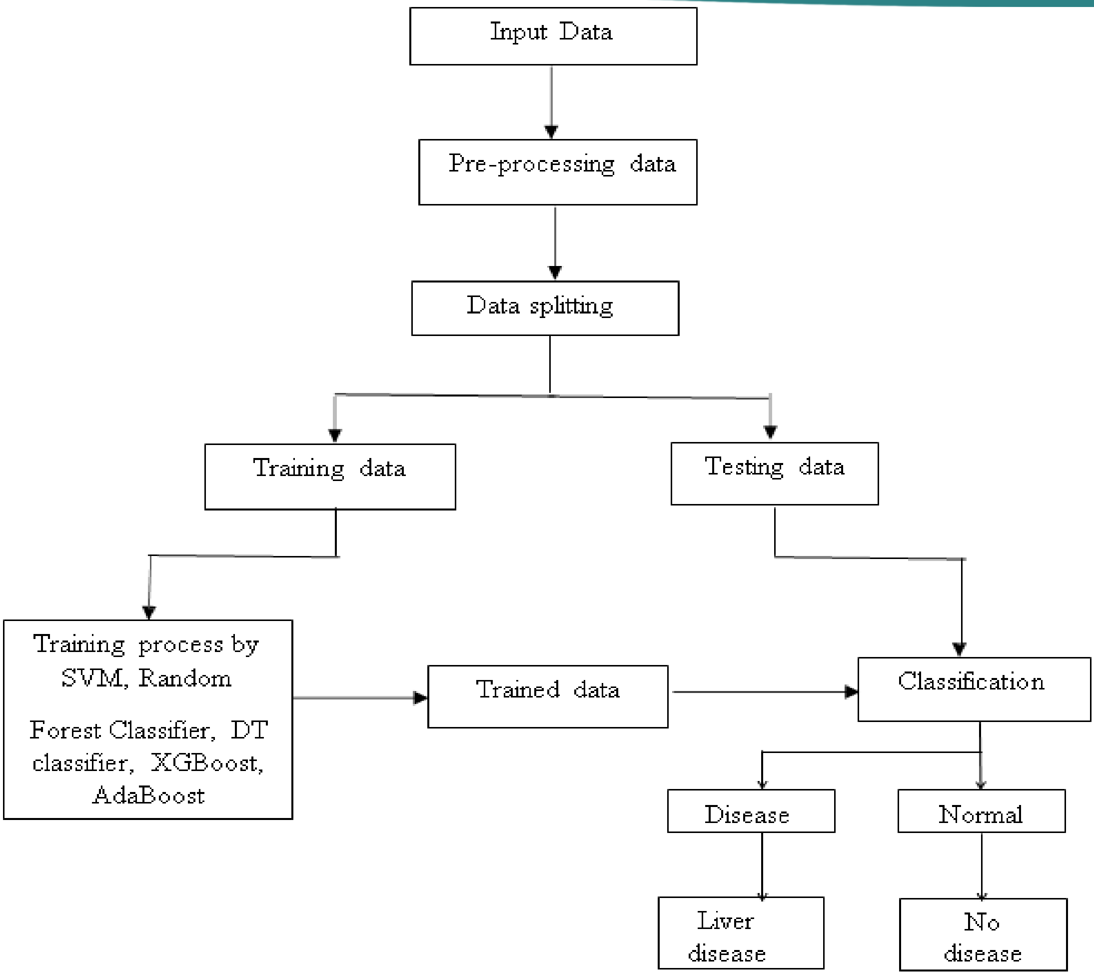

Figure 1. Proposed Model.

Splitting of Data

The dataset includes 615 patients and their medical characteristics. Training and testing sets had 492 and 123 samples, respectively. About 80% of the data is utilized to train models, allowing algorithms to find patterns and correlations between attributes and outcomes. The 20% testing set is kept separate during training and used just to evaluate the model. This organized strategy of separating data improves model development and prediction reliability by testing the model on separate data.

Assessment of Training

Processing the training data with various machine learning algorithms follows the train-test split. Datasets and issues may lend themselves more effectively to one method over another, and each algorithm has unique advantages. When these models are instantiated, the next step is to train them on data. This allows the algorithms to identify patterns and relationships. Fine-tuning the model parameters is necessary to minimize the discrepancy between the anticipated and actual results. Consequently, these trained models are employed for classification purposes, predicting the patient's condition based on the input features.

In the pre-processing of data, the relationship between the features is considered, which are as follows:

Figure 2 clearly shows a linear relation between ALT and AST, and Figure 3 shows a correlation between ALP and ALT.

The SVM model is subsequently trained and fitted using the training data. Following modeling, classification tasks are executed, and performance metrics, including recall score, accuracy score, and classification report, are produced. These evaluations yield detailed conclusions and results. Other machine learning techniques, such as the Random Forest Classifier, Decision Tree Classifier, XGBoost, and AdaBoost, are consistently implemented using this methodology. In conclusion, a comparative analysis is implemented to evaluate the efficacy of all models.

Experimental Results

In this section, all the experimental values concerning the different machine learning algorithms and their comparative study also discussed which ML algorithms show the best model to predict the liver disease. Figure 4 below shows the prediction of liver disease and the stage of the disease.

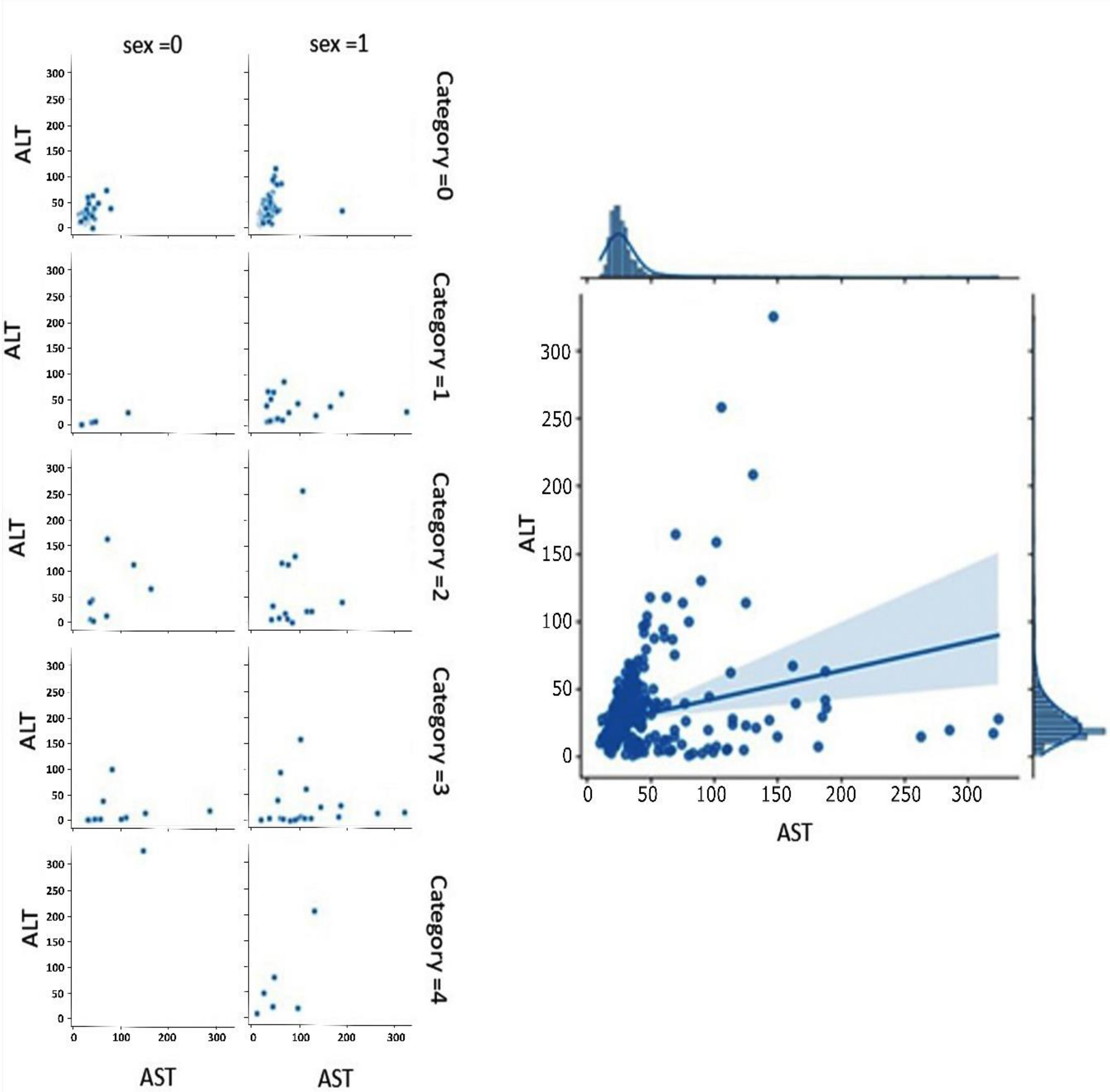

Figure 2. Relation between ALT & AST.

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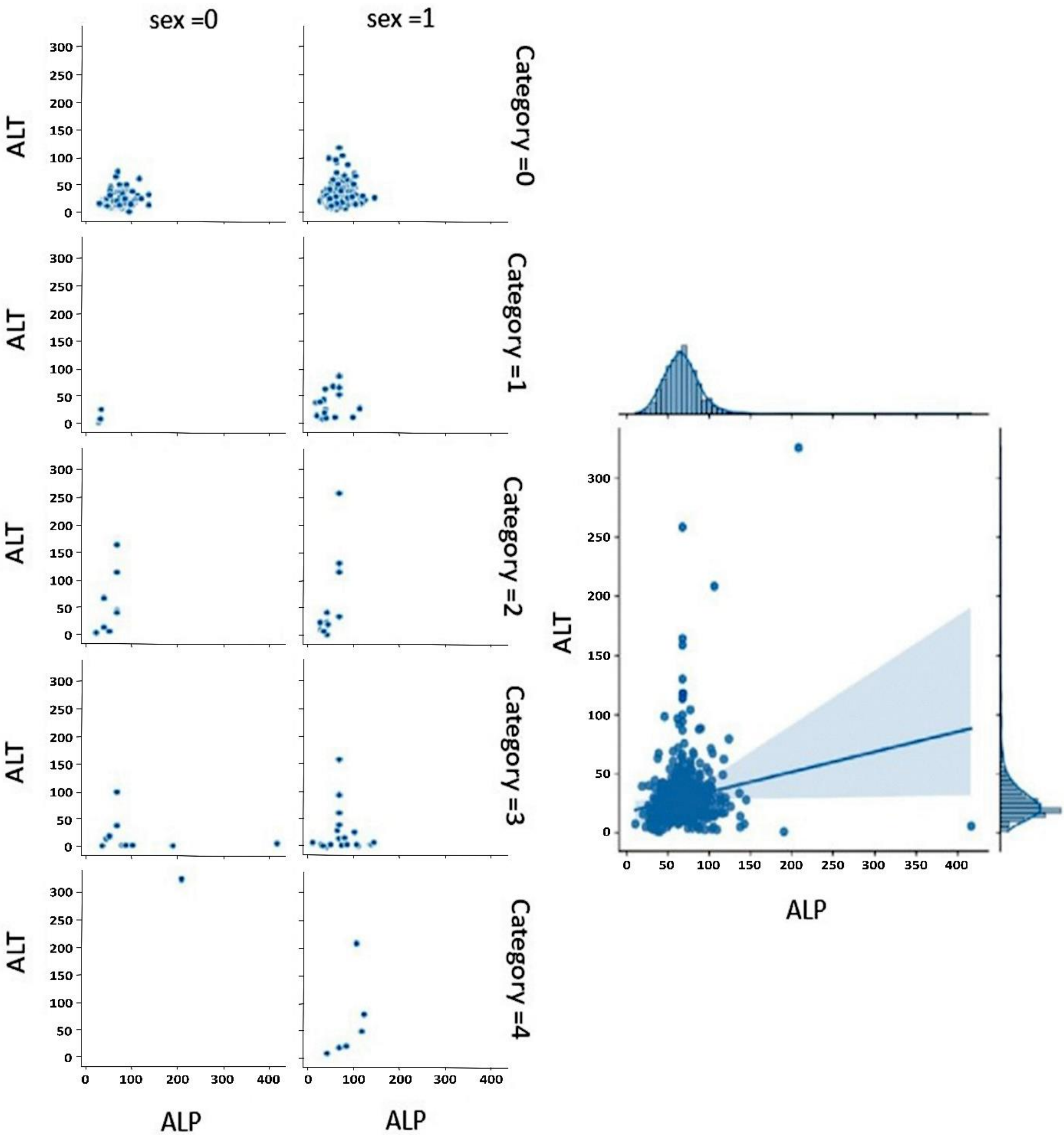

Figure 3. Relation between ALP & ALT.

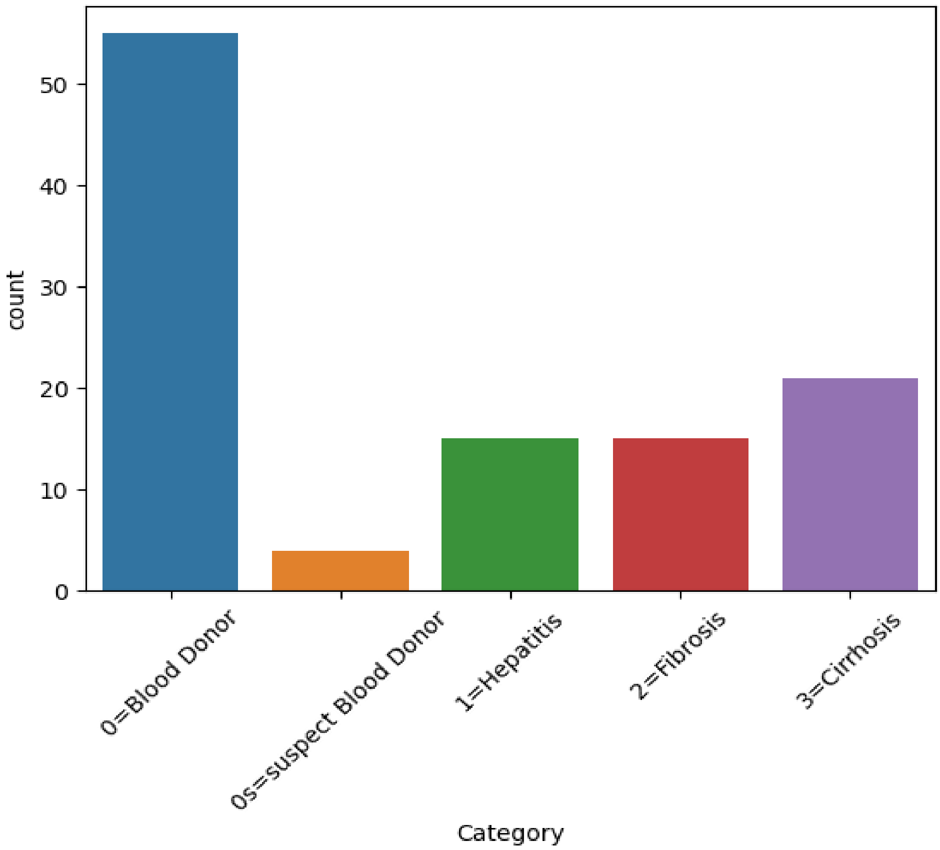

Figure 4. Classification of stage of the disease.

Category 0: Blood Donor (No disease)
Category 0s: Suspect Blood donor (Suspect disease)
Category 1: Hepatitis
Category 2: Hepatitis with fibrosis
Category 3: Hepatitis with fibrosis, cirrhosis

The classification with respect to gender and age is shown in below Figure 5.

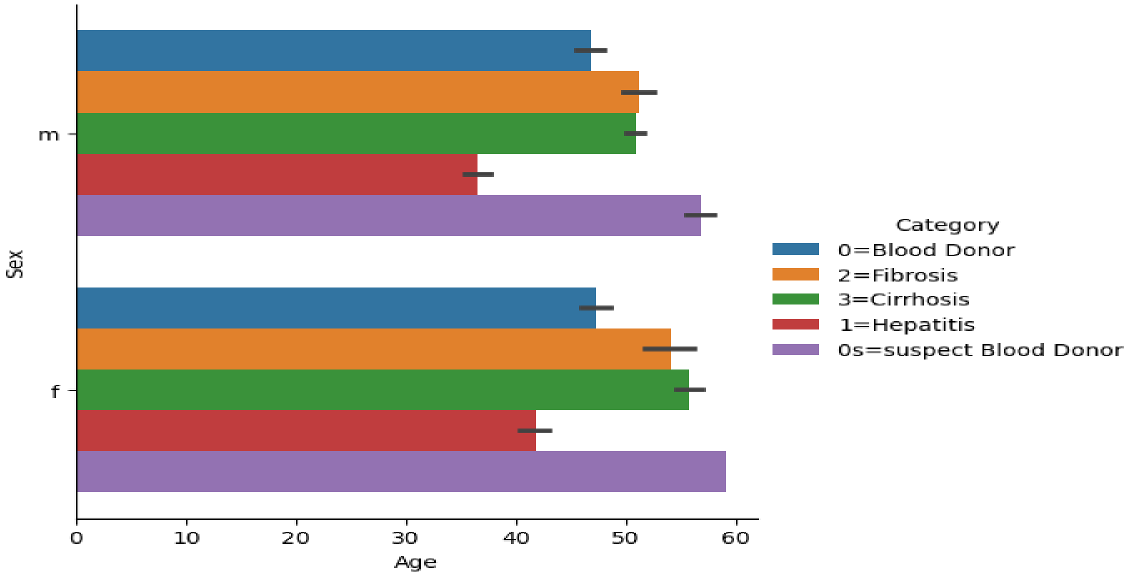

Figure 5. Classification based on sex, age and category.

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Table 1. SVM model performance metrics.

Accuracy	93.90 %
Precision	98%
Recall	67%
F1-score	80%

Confusion matrix is : [[55 0 0 0 0]
[0 1 2 0 0]
[0 0 9 0 0]
[0 0 0 6 0]
[1 0 0 2 6]]

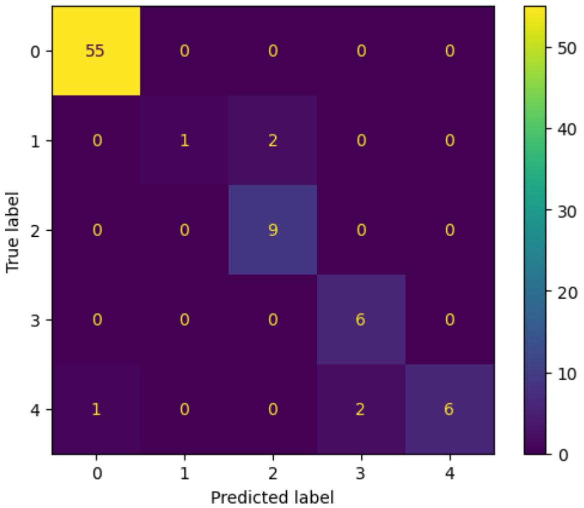

Figure 6. Confusion matrix using SVM.

Table 2. Random Forest Classifier performance metrics.

Accuracy	95.12 %
Precision	89%
Recall	78%
F1-score	88%

Confusion matrix is : [[55 0 0 0 0]
[0 2 1 0 0]
[0 0 8 1 0]
[0 0 0 6 0]
[0 0 0 2 7]]

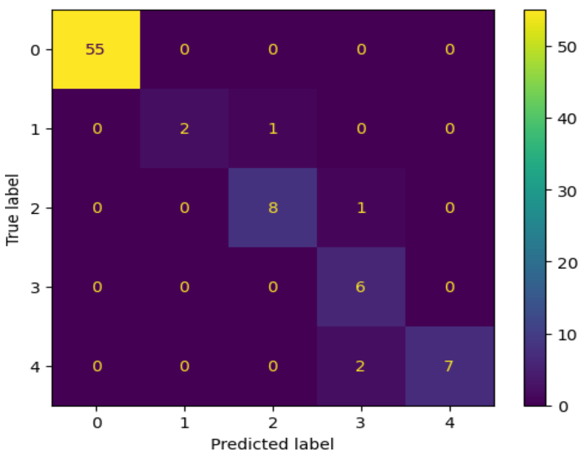

Figure 7. Confusion matrix using Random Forest Classifier.

Table 3. Decision Tree classifier performance metrics.

Accuracy	98.78 %
Precision	86%
Recall	89%
F1-score	92%

Confusion matrix is : [[55 0 0 0 0]
[0 3 0 0 0]
[0 0 9 0 0]
[0 0 0 6 0]
[0 0 0 1 8]]

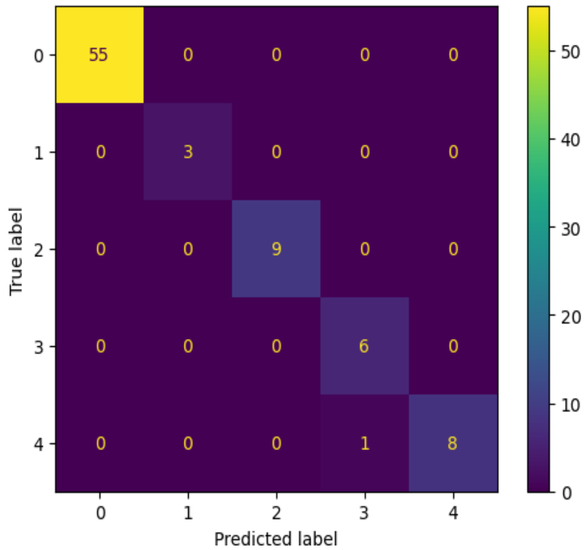

Figure 8. Confusion matrix using decision tree classifier.

Table 4. XGBoost performance metrics.

Accuracy	96.34 %
Precision	81%
Recall	83%
F1-score	90%

Confusion matrix is : [[55 0 0 0 0]
[1 1 1 0 0]
[0 0 9 0 0]
[0 0 0 6 0]
[0 0 0 1 8]]

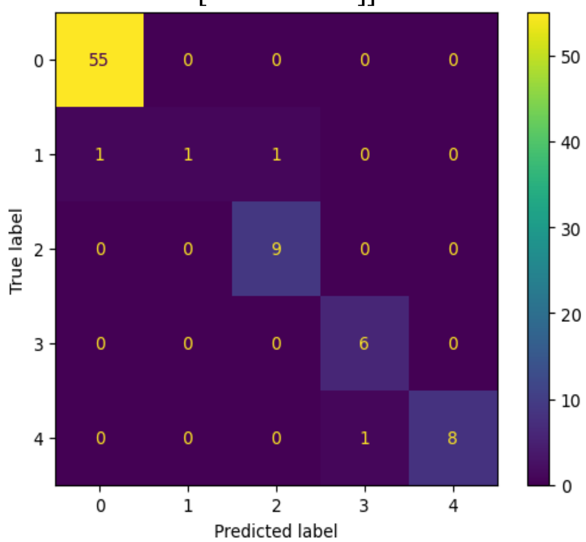

Figure 9. Confusion matrix using XGBoost.

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Table 5. AdaBoost performance metrics.

Accuracy	96.34 %
Precision	86%
Recall	89%
F1-score	94%

confusion matrix is : [[55 0 0 0 0]
[0 1 2 0 0]
[0 0 9 0 0]
[0 0 0 6 0]
[0 0 0 1 8]]

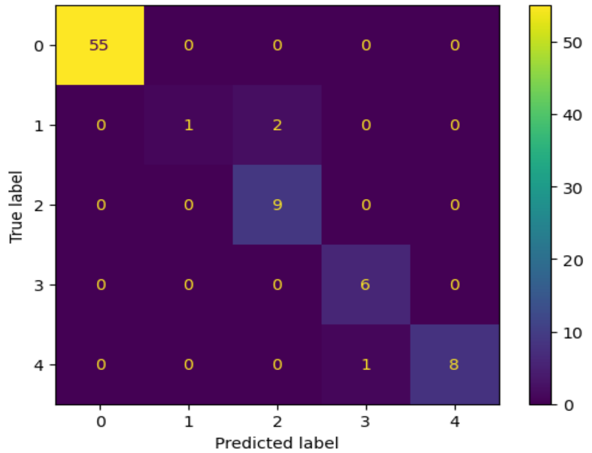

Figure 11. Confusion matrix using AdaBoost.

The comparison between the various models is shown in the Table 6.

Table 6. Comparative Analysis of Algorithms.

Method/ Parameter	Precision	Recall	F1-Score	Accuracy
Support Vector Machine	98%	67%	80%	93.90%
Random Forest Classifier	89%	78%	88%	95.12%
Decision Tree Classifier	86%	89%	92%	98.78%
XGBoost	81%	83%	90%	96.34%
AdaBoost	86%	89%	94%	96.34%

Conclusion

This study uses clinical and laboratory data to show how machine learning can predict liver disease. Highly accurate predictive models were created using decision trees, random forests, support vector machines, and ensemble learning. Precision data preprocessing, feature

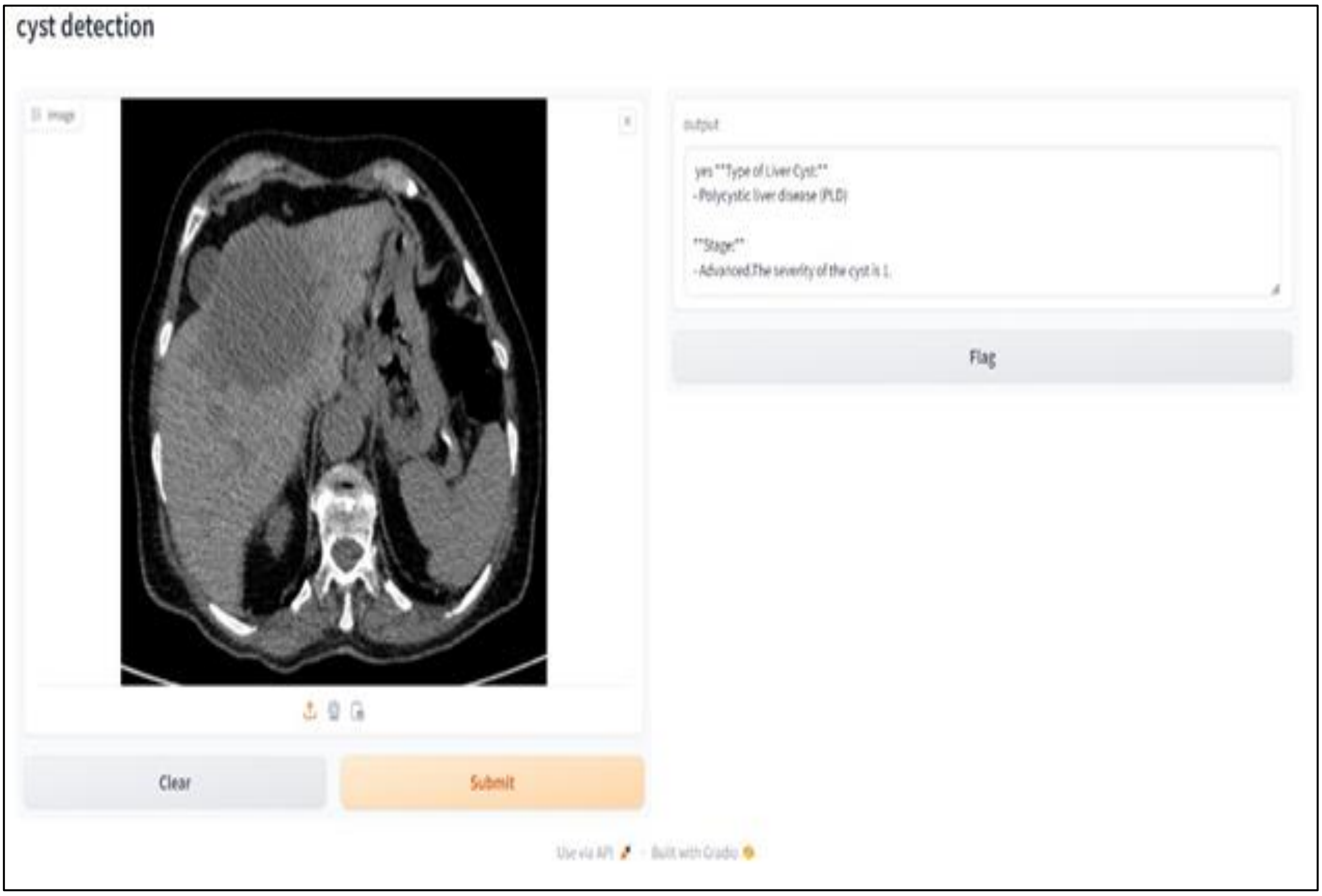

Figure 10. Cyst Detection.

engineering, and cross-validation optimised sensitivity and specificity. The findings show that machine learning can help doctors detect and treat liver disease early, enabling lifestyle changes. Early intervention is essential for patients and healthcare systems to reduce liver disease burden. The study also emphasizes the necessity to refine data and model performance to improve clinical applicability and the health condition of the patient with respect to liver disease can be predicted. If the patient has liver disease, then the stage of the disease can also be predicted by this proposed model. Also from various algorithms, the decision tree algorithm has the highest accuracy of 98.78% and is the best model to predict liver disease. In future work, we will work with an advanced deep learning model for accurate prediction of liver disease detection.

Conflict of Interest

Authors declare that there is no conflict of interest.

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