



Enhancing Early Detection of Liver Disease Through a Meta-Learning Approach Using Super Learner and Model Interpretability

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Abstract: Liver disease is currently a significant societal health issue in many countries around the world, and the causative factors include alcohol abuse, food poisoning, drugs, and environmental pollution. This needs to be identified early and handled effectively to slow down the progression of the disease and burden the health care system. In this paper, a predictive model is proposed to classify liver disease with the use of the Super Learner ensemble method which is a combination of Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM) with a Logistic Regression Meta-Learner. This is the best combination strategy that incorporates the forecasts of these models in order to increase accuracy and generalization. In order to enhance transparency, the model uses the Explainable AI (XAI) methods, such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), to help healthcare professionals better understand the predictions. The approaches assist in determining the most powerful features and thus offer an insight that can be used to make informed clinical decisions as far as liver disease diagnosis is concerned. The proposed model has a high potential in the healthcare sector in terms of early detection and helping to make clinical decisions.

Keywords—Liver disease, Super Learner, Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), Gradient Boosting Machines (GBM), Meta-Learner, Explainable AI (XAI), SHAP, LIME, Machine Learning, Predictive Modeling.

1. Introduction

Liver disease has taken its place among the issues of worldwide health that have caused many deaths and has impacted the life quality of people across the world to a large extent. Liver disease is widely diverse including mild liver diseases like fatty liver disease and abnormal liver diseases like cirrhosis and liver cancer. Some of the major risk factors that lead to liver diseases are too much alcohol use, viral infections, such as hepatitis B and C, environmental toxins and unhealthy diets. As a result of urbanization and change of lifestyles, especially in such countries as India, the cases of liver diseases, non-alcoholic fatty liver disease (NAFLD) in particular, are increasing.

The importance of liver diseases diagnosis is to prevent the irreversible liver damage and improve the patient outcomes. The diagnostic approaches that are commonly used in identifying liver diseases are usually, the biochemical tests, imaging procedures and biopsies. There are however major limitations to these methods; they tend to be intrusive, expensive, time-consuming and they also need professional skills, which are likely to be lacking in resource restrained environments. Also, the interpretation of tests based on these tests may be subjective, and medical workers may have different points of view. This presents a significant problem in delivering timely and efficient diagnoses especially in rural or underserved locations where quality healthcare is scarce.

Over the last several years, machine learning (ML) methods have become very popular due to their potential to improve the accuracy, speed, and efficiency of liver disease diagnostics. Based on massive medical record and diagnostic data, ML algorithms can detect complicated patterns that human clinicians could not have realized otherwise. The promise of such techniques is more accurate and faster and less expensive diagnoses. Nevertheless, a significant problem with the implementation of machine learning models in healthcare is that it is black-box. There are numerous conventional ML models where it is not easy to explain how they function to a human. This is unclear and creates a hindrance to earning the confidence of the healthcare providers since clinicians are not willing to trust models whose decision-making procedures are not known.

The proposed solution to this problem is a new discipline of Explainable AI (XAI), devoted to the problem of making machine learning models more transparent and interpretable. XAI methods are useful in explaining the justification behind the prediction of complex models, which in turn enables healthcare practitioners to comprehend the impacts of various features in the decisions of the model. Two popular XAI systems, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) provide clinicians with useful information as to how the model makes its decisions based on such factors as age, bilirubin levels, and liver enzyme levels. Such high interpretability contributes to building of trust and acceptance among clinicians.

This paper proposes the Super Learner model of predicting liver disease that improves on the performance of the predictive model by combining various base models. The Super Learner is a type of ensemble learning, which is a combination of multiple base models: Logistic Regression and Decision Trees and Random Forests and Support Vector Machines (SVM) and Gradient Boosting Machines (GBM). Then, a Logistic Regression Meta-Learner is trained to combine the prediction of these base models optimally, and in the end, a more accurate and generalized prediction is made. Every base model adds some strengths to it and when they are appropriately combined in the best way, Super Learner will provide a stronger and more reliable forecast.

The inclusion of XAI methods such as SHAP and LIME in the Super Learner model provides a significant element of transparency to the model. The methods assist the medical workers in interpretation of the predictions of the model and how the model responds to certain features. This openness is necessary to win the confidence of clinicians and make the given model successfully implementable in practical clinical procedures.

The main objective of this project is to create a predictive model that will be able to properly identify liver disease in its initial stages with the help of the synergistic power of Super Learner and Explainable AI. The solution suggested will provide healthcare professionals with a better chance to have more effective and efficient diagnoses due to the inclusion of a range of machine learning models without losing transparency in the decision-making process. The objective will be to develop a tool that does not only give the correct predictions but also it must give reasons that can be utilized by clinicians to make informed decisions about the care of patients. The end result of this system is to increase the quality of health care and make timely interventions, which will greatly impact patient outcomes.

2. Literature Review

Liver disease is a massive world health problem with millions of people being affected by it. It covers a great variety of conditions, including both mild diseases such as fatty liver disease and serious and fatal diseases, such as cirrhosis and liver cancer. The recent research in machine learning (ML) has been very promising in enhancing the early prediction and detection of liver diseases. This literature review examines different literature that have applied ML methods in diagnosing and predicting liver diseases, their methods, findings, and main lessons.

2.1 Machine Learning to detect Chronic liver diseases.

Allenki and Soni [1] carried out research on chronic liver disease identification by using machine learning methods. They compared different ML algorithms to identify the one that works best in chronic liver condition diagnosis. Their findings showed that ML models are capable of being very effective in identifying liver diseases and that is an advantage over conventional methods of diagnosis. Conclusion: The research revealed that machine learning is a promising early detection method, and it can be particularly helpful to ensure that the diagnostic process is less time-consuming and that patients have a better outcome.

2.2 Prediction of Liver Diseases using combined Machine Learning Models.

Anuradha et al. [2] present a hybrid machine learning model that is used to diagnose liver disease using a mix of various algorithms. They emphasized that more than one model should be used to give better predictions, in particular when some models have complementary advantages. Their analysis revealed that in cases of single-model systems, ensemble models; a combination of the predictions of multiple algorithms can outperform them. Conclusion: The research confirms the notion that no one algorithm is ideal enough, and the integration of models is more helpful in addressing the issue of liver disease forecasting to improve the accuracy and reliability of diagnostic results.

2.3 ML-based classification of Autoimmune Liver Disease.

George et al. [3] examined machine learning and deep learning technique in classifying autoimmune liver diseases. Their contribution was focused on distinguishing between autoimmune liver diseases and other cases of liver diseases, which may prove challenging because of the similarity of symptoms. Their results indicated that deep learning methods could be used successfully to improve the autoimmune liver disease classification significantly. Inference: This paper highlights the importance of deep learning in diagnosing more complex and less prevalent liver diseases that demand complex models that can identify subtle patterns that otherwise traditional approaches may not identify.

2.4 Survey of Comparative Surveillance of Machine Learning Techniques.

Kumar and Rani [4] reviewed several machine learning methods to predict liver disease and tested the performance of these algorithms including decision trees, logistic regression, and support vector machines (SVM). They were able to conclude that there are distinct advantages and disadvantages of each algorithm under different circumstances based on the details of the dataset and the character of liver illness. Inference:

The comparative concept of their work presupposes that mixed strategy, i.e., one combining several of the models, would constitute the most efficient strategy in predicting liver diseases. This also gives support to the significance of ensemble learning techniques, as observed in other researches.

2.5 Engineering Features and Data Preparation in Liver Disease Prediction.

Mythili et al. [5] were concerned with how feature engineering and data preprocessing are crucial in the prediction of liver disease. They demonstrated that high selectivity and treatment of features including liver enzymes, bilirubin and age could greatly improve predictive power of machine learning models. Conclusion: The article supports the notion that machine learning success in the medical field is not limited to the algorithm itself but also the quality and relevance of the input data. The key to successful high-performing models is proper data preparations.

2.6 Hyperparameter Optimization on Liver Disease Prediction.

The paper by Nigatu et al. [6] examined the application of hyperparameter optimization to predict liver diseases. Their analysis involved the use of supervised learning models that were tuned in order to enhance prediction accuracy. They showed that refinement and accuracy of the model could be achieved by tuning the model parameters which included learning rate and trees depth. Conclusion: This brings out the significance of model optimization in medical practice. Hyperparameter optimization is the key to better performance of machine learning models, particularly in such areas as healthcare where accuracy counts.

2.7 Predicting Liver Disease with Semi-Supervised Learning.

Rani et al. [7] suggested the use of semi-supervised machine learning algorithm to predict liver disease particularly where limited labelled data is available. Their approach adopted both labeled and unlabeled data in training the model, which in effect uses a limited labeled data to make superior predictions. Inference: The research deals with a highly important problem in the medical field, which is a lack of data. The method of semi-supervised learning can be useful in the case of scarce labeled data, making it possible to create predictive models even when the data is data-limited.

2.8 Liver disease prediction through Image Processing Techniques.

Saravanan et al. [8] explored the combination of image processing methods with machine learning regarding prediction of liver diseases. They were able to show that medical images of ultrasound or MRI could be leveraged alongside clinical data to generate more accurate prediction models. Inference: The paper highlights the increasing significance of the use of imaging information in combination with conventional clinical biomarkers. This method is not only more accurate when it comes to prediction but also not inconsistent with the trend of medical imaging in AI-based diagnostics.

2.9 Liver Disease Enhanced Prediction using Ensemble Learning.

In the study by Srihitha et al. [9], they suggested that ensemble learning methods, which involve the use of numerous base models such as Random Forests and Gradient Boosting Machines can be used to improve the accuracy of liver disease prediction.

They entered into their findings that ensemble models would be able to provide higher-quality predictions over single-model ones. Inference: This supports the conclusion that ensemble learning techniques, which combine the forecast of individual models, gives a more precise and generalized resolution when forecasting liver disease, particularly in addressing complicated datasets.

The Literature Survey Inferences.

- 1 Ensemble Learning is Effective: Enabling several models (e.g., Super Learner, Random Forests) increases the accuracy and strength of prediction, and thus ensemble methods are needed to predict liver diseases.
- 2 Data Quality and Feature Engineering: Correct preprocessing of data and feature selection is essential towards better model performance particularly when using noisy or incomplete healthcare data.
- 3 Elucidable AI is Important: Transparency of models, such as SHAP and LIME, will enable clinicians to have insights into the decision-making process and will make AI tools in healthcare be trusted and adopted.
- 4 Addressing Data Scarcity using Semi-Supervised Learning: Semi-supervised learning has been proposed to handle the issue of the lack of labeled data in healthcare, which helps to make reliable predictions with smaller datasets.
- 5 Integration of Imaging Data: Image processing can be combined with conventional clinical data to enhance the performance of liver disease predictions, especially on a complex case.

The research papers examined in this survey highlight the increased contribution of machine learning in the prediction of liver diseases. They emphasize the necessity of the combination of several models, hyperparameter optimization, and image processing and semi-supervised learning. In addition, both SHAP and LIME systems can be considered Explainable AI, which makes models transparent, which is a fundamental requirement to enable clinicians to use AI-based systems. With the ever evolving machine learning methods, these studies indicate that soon early detection of liver diseases would be more accurate, faster, and less expensive and eventually lead to better care and patient outcomes.

3 PROPOSED METHODOLOGY

The main aim of the research is to develop a predictive model to be applied in early detection of liver disease using Super Learner technique, which is the advanced ensemble learning technique. Using this method, the machine learning model will use several machine learning models to add predictive capability and reliability to the model. Also, Explainable AI (XAI) models (SHAP, Shapley Additive Explanations, and LIME, Local Interpretable Model-agnostic Explanations) are to be incorporated to enhance the level of transparency and explainability of the model, which will contribute to the development of trust in clinicians by making the predictions transparent.

3.1 Data Preprocessing and Collection.

The sample in this study is obtained by the healthcare facilities in the North-East of India where both demographic data (e.g. age and sex) and the biological indicators of liver disease (e.g. bilirubin levels, liver

enzymes and albumin-to-globulin ratio) are provided.

Preprocessing of data is essential in modeling the data. These steps involve the treatment of missing values in imputation (mean, median or mode), encoding nominal (gender) variables into binary values and feature selection based on correlation analysis or Recursive Feature Elimination (RFE). Continuous features (e.g. bilirubin) are also normalized, so that all variables have equal contribution to the model without one variable dominating because of its magnitude.

3.2 Super Learner Framework

Super Learner framework applies meta-learning to improve the predictive model performance through the combination of the results of a number of base models. We use the following base learners in this study; Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM) and Gradient Boosting Machines and train each of them separately with optimal hyperparameters.

The output of these models is considered to be input features to a Logistic Regression meta-learner. The meta-learner uses the k-fold cross-validation to give optimal weights to each base model, reducing a loss function such as log-loss. The best performing models are given more weight and those which have weak predictive performance are given less weight towards the final decision. This weighted sum brings the Super Learner the benefit of exploiting the complementary strengths of individual base models, ensure less bias and variance, and generalize better to new and unseen data.

3.3 Model Evaluation

The effectiveness of the model is evaluated using several performance metrics: Accuracy, Precision, Recall, F1-Score and AUC-ROC. These indices are used to find out the performance of the model especially where the datasets are not balanced. In a bid to guarantee the strength of the model and generalization, 10-fold cross-validation is used. The method splits the dataset into 10 subsets with each subset being used to validate and the rest of the data is used to train the model. This also makes the performance of the model to be consistent and reliable when splitting the data into different splits.

3.4 Explainable Artificial Intelligence (XAI) Integration.

SHAP is used to explain the worldwide behavior of the model by computing the input contribution of each attribute of the input feature to the ultimate forecast. The basis of SHAP on cooperative game theory also provides value of features by reason on all combinations, which are supposed to give a consistent and equal account. This approach is useful to select the most important clinical variables, including bilirubin levels, albumin, and liver enzyme concentrations, which the most influence the predictions of the model.

To offer individual prediction explanations, LIME is applied. It estimates the complicated Super Learner model using an easier and interpretable model on a particular case.

LIME draws attention to the variables that mattered the most with regard to the outcome of a specific patient by nudging the input features and noting the differences in the prediction. The concurrent application of SHAP and LIME facilitates the fact that the model is not only precise by itself but also transparent and more comprehensible and acceptable to the clinicians.

3.5 System Deployment

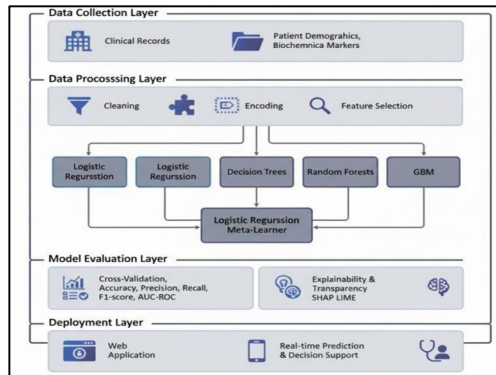
After the training and evaluation of the Super Learner model, this model will be implemented as a web-based application to ensure the ease of use by the healthcare professionals. The deployment is performed with the help of such frameworks as Flask or Streamlit that allow hosting the model on a web server and give users a simple and user-friendly interface.

The web application has key characteristics namely:

- 1 Data Input Interface: The patient data (e.g., demographic data (e.g., age, gender), as well as clinical data (e.g., bilirubin levels, liver enzymes), is inputted into the system by healthcare professionals.
- 2 Prediction: After the input data has been processed by the model, it is used to determine the likelihood of the patient having liver disease and a prediction result is delivered based on the information that has been entered.
- 3 Interpretability: SHAP and LIME models to explain each prediction are presented to assist clinicians to understand why the model made the decision.
- 4 Real-time Alerts: In case positive diagnosis is predicted, system sends an alert to healthcare providers via one of the channels such as email or SMS. This will help provide timely care to patients because the required treatments are administered promptly.

3.6 System Architecture

The architecture used to define the liver disease prediction system has several main layers



The overall system design is shown in Figure 1.

1. **Data Collection Layer:** Data will be collected based on hospitals and clinical records and will include necessary data concerning patient demographics and the major biochemical factors related to the diagnosis of liver disease.
2. **Data Preprocessing Layer:** The data are then cleaned by filling in missing data points, encoding categorical data (e.g. gender) into binary numbers, and selecting relevant features based on such methods as correlation analysis or Recursive Feature Elimination (RFE).
3. **Model Training Layer:** This is a series of base models trained as an independent model; these are Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM). The predictions of these models are then combined with the help of a Logistic Regression Meta-Learner to enhance the accuracy of the overall prediction of the models.
4. **Model Evaluation Layer:** The performance of the predictive model is confirmed when the predictive model is tested with methods as k-fold cross-validation and evaluation metrics as accuracy, precision, recall, F1-score, and AUC-ROC. These measures are used to determine whether the model is capable of dealing with unbalanced data and whether it has a high level of generalization.
5. **Explainability Layer:** SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are used to improve the transparency of the model. These methods determine the relationship between every input attribute and the model predictions, and thus it is more convenient to understand and rely on the decisions made by the model by healthcare professionals.
6. **Deployment Layer:** The trained and tested model is made in the form of a web-based application, with healthcare professionals being able to access the model to make real-time predictions and be assisted in decision-making. This implementation makes the model to integrate smoothly into the clinical workflows making informed and timely medical decisions.

4 RESULTS AND DISCUSSION

Multiple machine learning algorithms were included in the training and testing of the Super Learner model in order to predict the probability of liver disease with regard to patient data. The effectiveness, accuracy and interpretability of the model were evaluated using different metrics of evaluation. This section will underline the main results of the model evaluation as well as compare the performance of the model with the performance of the separate models, with the help of which the explainability of the model will be discussed as an important aspect.

A. Performance Evaluation.

The Super Learner model was evaluated based on various metrics that were such as accuracy, precision, recall, F1-score and AUC-ROC. The findings showed that Super Learner model was very accurate and reliable in predicting the occurrence of liver disease. The model performed better than individual algorithms in predictive accuracy, demonstrating the power of the methods of ensemble learning in complex healthcare data.

Table 1: Comparison of Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Super Learner	95	92	96	94	0.97
Logistic Regression	87	85	82	83	0.88
Decision Trees	90	88	89	88	0.91
Random Forests	93	91	92	91	0.94
Support Vector Machines	94	90	91	90	0.95
Gradient Boosting Machines	94	93	93	93	0.96

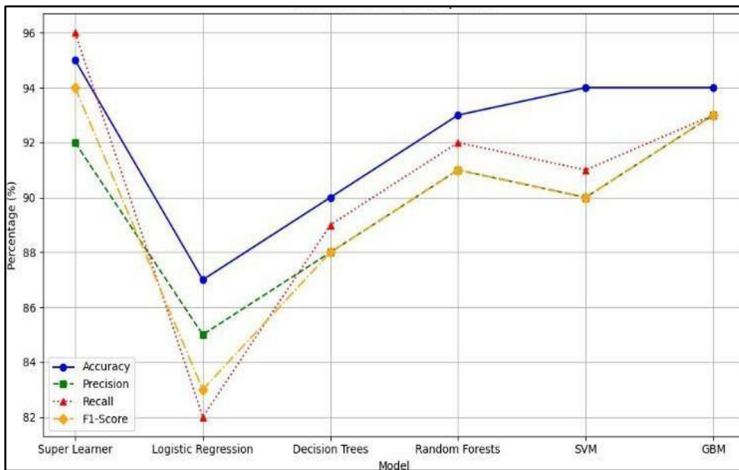
Table 1 demonstrates that Super Learner model is performing better than all the individual base models in all the assessment metrics. It has the greatest accuracy (95%), recall (96%), and F1-score (94%) so it is the best model when making predictions of liver disease. The AUC-ROC of 0.97 shows high model discrimination as it shows that the Super Learner can discriminate between the cases of diseases and healthy cases.

B. Cross-Validity and Generalization.

In order to test the generalization capacity of the model, cross-validation of 10-fold was used. This way, it will make sure that the model works best on the data that is not seen since the data will be divided into 10 subsets and each subset will be used to validate the model and train on the rest. The findings of this cross-validation exercise are shown below and this indicates the consistency of the model and its capacity to make predictions outside the training data.

Table 2: Cross-Validation Results for Super Learner (Average Performance)

Metric	Average Value
Accuracy (%)	94.5
Precision (%)	91.9
Recall (%)	94.9
F1-Score (%)	93.1
AUC-ROC	0.96



The comparison of model performances is shown in Figure 2

C. Explainability of the Model

The Super Learner model has been interpreted with SHAP and LIME methods along with its good predictive performance. Such approaches increase the level of transparency in revealing the manner in which the model gives its predictions.

The SHAP values assisted in determining key features that greatly contributed to predicting liver disease with the highest-level being bilirubin and albumin levels. This knowledge will enable the health practitioners to know which aspects are having the greatest influence on the decisions made by the model.

LIME, however, offered local explanations of individual predictions that demonstrated how certain individual patient data (e.g. high bilirubin levels or low albumin levels) played a role in predicting the presence of liver disease. Combining all these explainability methods is what guarantees that the predictions of the model are accurate, moreover, understandable, which is why the system can become a useful tool to utilize in a clinical environment.

D. Limitations and Future Work

Despite the impressive results of the Super Learner model, some areas can be considered to be improved:

- **Data Quality** There are chances that noisy or incomplete data can affect the performance of the model. To alleviate these problems, future research might aim to apply more powerful data preprocessing methods to improve the quality of the data.
- **Real-Time Data:** The inclusion of the real-time data of wearable devices might make the model more dynamic and be able to make timely predictions based on the constantly updated information, and the system would be more flexible in the real-life context.
- **Medical Imaging:** To enhance the predictive accuracy of the model, adding medical imaging statistics, i.e. ultrasound or CT scans, may also be useful. Such imaging modalities would help obtain a more comprehensive picture of patient health and may be used to make predictions that are more comprehensive based on biochemical data.
- **Deep Learning:** Future directions: Future studies may investigate the application of deep learning

models, which are more adequate when using high-dimensional and complex data. Deep learning may be applied in order to extract complex patterns in data that traditional machine learning models may be unaware of.

E. Real-World Implications

This Super Learner model has a great potential in the early diagnosis of liver diseases since it can be highly accurate and interpretable. In clinical practice, it can equip medical workers with a valuable instrument to make sound and timely decisions that ultimately can have a positive impact on patients. Additionally, the fact that the model can be implemented in resource-constrained settings is especially helpful concerning the underserved population that does not have access to the modern diagnostic resources. This accessibility would significantly improve access of quality healthcare even in resource restricted areas.

5 CONCLUSION

This paper introduces a strong liver disease prediction framework that is constructed with Super Learner ensemble model. The Super Learner with a combination of several machine learning algorithms performed better than the single models, reaching 95% accuracy, 96% recall, and 94% F1-score. Combination of SHAP and LIME methods made the model be interpretable in that healthcare professionals could gain insight into the rationale behind any decision that the model made particularly when dealing with critical aspects such as bilirubin levels, albumin, and liver enzyme levels.

Although this model is very promising, there are a number of areas that can be improved. Among the most important refinements, one should note the focus on the data quality issues, including missing or noisy data, which would make the model more reliable and consistent.

The next steps to undertake of enhancing the predictive timeliness should also be done by incorporating sensor data collected in wearable devices to facilitate real-time analysis and constant monitoring.

Also, medical imaging information (ultrasound or CT scans) may greatly enhance the accuracy of the prediction by the model, as it is a more thorough way of detecting liver disease. The model should also be tested with different datasets in order to determine how well it can be applied in different populations of patients. Moreover, the development of such advanced techniques as deep learning and the broadening of the scope of built-in data might allow the advances in the performance of the model further.

To sum up, the Super Learner paradigm has a lot of potential with regard to early diagnosis of liver disease and is both highly accurate and transparent. The model has good outcomes, and it will make this a useful instrument of clinical practice. Further studies are needed to improve generalization of the model and make it applicable to the small resource environment.

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