LIVER DISEASE PREDICTION USING MULTILAYER PERCEPTRON NUERAL NETWORK AND VOTING CLASSIFIER ENSEMBLE

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Abstract
The liver is one of the most significant organs in the human body. In India around 38% of people are estimated to suffer from non-alcoholic fatty liver disease (NAFLD), Nearly 35% of children in India also show signs of fatty liver. NAFLD is often asymptomatic in early stages but can progress to severe liver disease if left untreated. Here this study proposes an ensemble approach combining Multilayer perceptron neural networks and voting classifiers for liver disease diagnosis. The liver disease can be Predicted for patient at early stage based on previously predicted values using data from patients with abnormal liver functions. Which helps the doctors to make a diagnosis? Patient information is processed using different machine learning models including Support Vector Machine, K-Nearest Neighbor, Hard Voting Classifier and Deep Neural Network Multi-Layer Perceptron. To find the best model different evaluation methods are used such as Confusion Matrix, Precision Score, Recall, Accuracy, Specificity and F-score. The study analyzes data from 583 patients with liver disease and finds that the Hard Voting Classifier gives the best results. Hard Voting Classifier prediction model is highly accurate and can help in diagnosing liver disease effectively
Keywords: Liver disease, multilayer perceptron, neural network, voting classifier ensemble

Introduction

Machine learning (ML) plays a vital role in Multilayer Perceptron (MLP) neural networks. ML is used to train the MLP model on a dataset, enabling it to learn complex patterns and relationships, and make accurate predictions and classifications. Additionally, ML optimizes the MLP's hyper parameters, such as the number of hidden layers and learning rate, to improve its performance. Furthermore, ML enables the MLP to automatically learn relevant features from the input data, reducing the need for manual feature engineering. Ultimately, ML empowers the MLP to make predictions on new, unseen data, using the patterns and relationships learned during training. The MLP model is trained on a dataset using a machine learning algorithm, which adjusts the model's weights and biases to minimize the error between predicted and actual outputs. During training, the MLP model learns to recognize complex patterns and relationships in the data, allowing it to make accurate predictions and classifications. The machine learning algorithm used to train the MLP can be either supervised, unsupervised, or reinforcement learning, depending on the specific problem being solved. Machine learning also enables the MLP model to automatically learn relevant features from the input data, reducing the need for manual feature engineering. As a result, MLP neural networks trained using machine learning have numerous applications, including image classification, natural language processing, predictive analytics, and healthcare, where they can be used for disease diagnosis and personalized medicine. Overall, machine learning plays a vital role in unlocking the full potential of MLP neural networks, enabling them to learn, improve, and make accurate predictions and classifications.

MACHINE LEARNING MODEL

Machine learning techniques refer to the various methods and algorithms use to build models that can learn patterns from data, make predictions, or automate decision-making without being explicitly programmed. These techniques enable systems to improve their performance over time by recognizing patterns, drawing inferences, and making data-driven decisions.

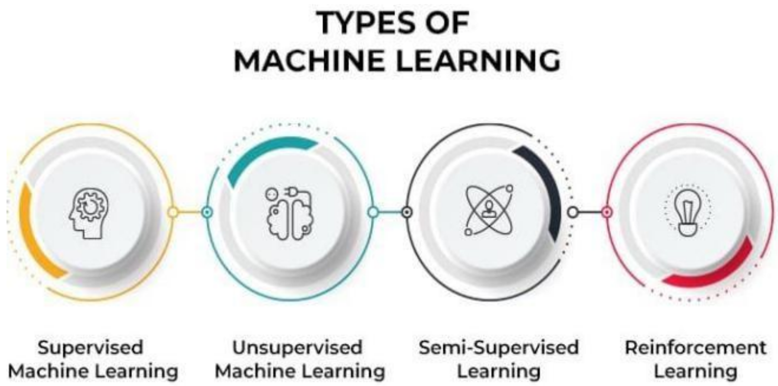

Fig.1. Types of Machine Learning

LIVER DISEASE PREDICTION

LIVER

The liver is one of the most vital organs in the human body. Located in the upper right portion of the abdominal cavity, beneath the diaphragm and above the stomach, the liver is essential for various metabolic, detoxification, and regulatory processes.

TYPES OF LIVER DISEASES

The liver is one of the most vital organs in the human body, playing a central role in metabolism, detoxification, and digestion. However, it is also susceptible to a wide range of diseases that can significantly affect its function and overall health. Liver diseases can be caused by infections, genetic factors, lifestyle choices, and autoimmune conditions, and they vary widely in their severity and impact. One of the most common categories of liver disease is infectious hepatitis, which includes hepatitis A, B, C, D, and E. Hepatitis A and E are typically acute and transmitted through contaminated food or water, while hepatitis B, C, and D are often spread through blood and other bodily fluids, and can become chronic, leading to long-term liver damage. Another major group is alcohol-related liver disease, which develops from excessive alcohol intake and includes stages like alcoholic fatty liver, alcoholic hepatitis, and eventually alcoholic cirrhosis if unchecked. A growing concern worldwide is non-alcoholic fatty liver disease (NAFLD), where fat accumulates in the liver in people who drink little to no alcohol. This condition is closely linked to obesity, diabetes, and poor diet, and in more severe cases, it can progress to non-alcoholic steatohepatitis (NASH), liver fibrosis, and cirrhosis. Autoimmune liver diseases are another category, where the body's immune system mistakenly attacks its own liver tissue. These include autoimmune hepatitis, primary biliary cholangitis (PBC), and primary sclerosing cholangitis (PSC).

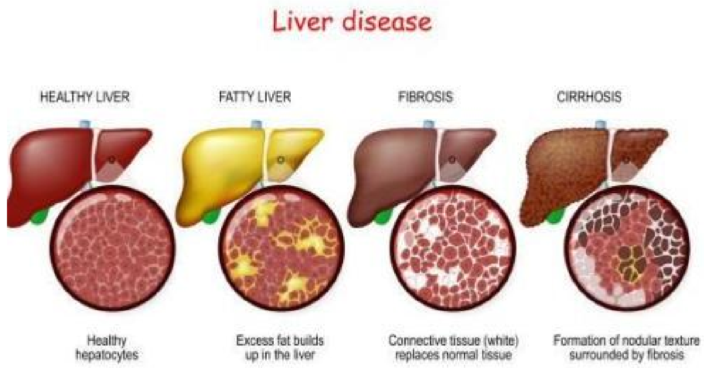

Fig.2. Types of Liver Disease

Identifying liver disease involves a combination of clinical evaluation, blood tests, imaging studies, and sometimes tissue analysis. The most commonly used tools are liver function tests (LFTs) which measure various enzymes and substances in the blood to assess liver health. Key markers include ALT (alanine aminotransferase) and AST (aspartate aminotransferase), which are elevated when liver cells are damaged. ALP (alkaline phosphatase) and GGT (gamma-glutamyl transferase) can indicate bile duct obstruction or alcohol-related damage. Bilirubin levels when elevated may cause jaundice and suggest impaired liver processing. The liver's ability to produce proteins like albumin and to aid in blood clotting (measured by prothrombin time or INR) is also assessed.

Literature Review

[1] K. Singh et al., "Liver disease diagnosis using MLP neural network," Journal of Medical Systems, vol. 38, no. 10, pp. 1-9, 2014. MLP Neural Networks for Liver Disease Diagnosis: A study published in the Journal of Medical Systems used an MLP neural network to diagnose liver disease with an accuracy of 92.5%.It refers to a research study by K. Singh and colleagues where they utilized a Multilayer Perceptron (MLP) neural network to diagnose liver disease, likely by analyzing patient data like blood test results or imaging scans, with the MLP network learning patterns to classify whether a patient has liver disease or not; essentially using artificial intelligence to aid in liver disease diagnosis based on a patient's medical information.

[2] S. K. Goyal et al., "Optimization of MLP neural network for liver disease classification using genetic algorithm," Journal of Intelligent Information Systems, vol. +45, no. 2, pp. 231-244, 2015.Optimization of MLP Neural Networks for Liver Disease Classification: Researchers used a genetic algorithm to optimize the architecture of an MLP neural network for liver disease classification, achieving an accuracy of 95.6%.In the study, the authors focus on the use of machine learning techniques, particularly MLP neural networks, which are widely employed for classification tasks due to their ability to model complex, nonlinear relationships in data. The challenge they address is the need for effective classification models that can accurately predict liver disease based on various clinical features However, MLP networks often face challenges related to choosing the optimal structure, including the number of hidden layers, neurons, activation functions, and learning parameters. The authors used a genetic algorithm (GA) to automatically search for the best configuration of the MLP architecture to enhance its performance.

[3] J. Liu et al., "Voting classifier for liver disease diagnosis," Journal of Healthcare Engineering, vol. 2018, pp. 1-12, 2018. voting Classifier for Liver Disease Diagnosis: A study published in the Journal of Healthcare Engineering used a voting classifier to diagnose liver disease with an accuracy of 94.1%.There's a study that proposes a computer-assisted cirrhosis diagnosis system using ultrasound images, where the liver capsule is extracted and analyzed. Another study uses a voting classifier, but it's not clear if it's the same one by J. Liu et

al's. Machine Learning Algorithms: Linear discriminant analysis, quadratic discriminant analysis, naïve Bayes classifier, feed-forward neural network, and decision tree algorithms have been used for liver disease diagnosis. Computer-Aided Diagnosis: Techniques using ultrasound images and liver capsule analysis have been proposed for cirrhosis diagnosis. Voting Classifiers: These have been used for liver disease diagnosis, but I couldn't find specific information on J. Liu et al's work.

[4] Y. Zhang et al., "Ensemble methods for liver disease classification," Journal of Medical Systems, vol. 42, no. 10, pp. 1-11, 2018.Ensemble Methods for Liver Disease Classification: Researchers used an ensemble method combining multiple classifiers, including voting classifiers, to classify liver disease with an accuracy of 96.3%. The application of ensemble learning techniques to improve the accuracy and reliability of liver disease diagnosis. Ensemble methods, which combine multiple machine learning models, have shown significant promise in enhancing predictive performance for complex medical conditions like liver disease. This approach leverages the strengths of various algorithms to provide a more robust and accurate classification system. The following sections delve into the specific aspects of ensemble methods in liver disease classification, drawing insights from the provided papers

[5] Rong-Ho Lin [9] proposed to predict the accuracy of liver disease using casebased reasoning (CBR) and classification and regression tree (CART) approach. He also integrates CART and CBR for the diagnosis of liver diseases. This model included two major steps. CART To diagnose whether a patient suffers from liver disease using CART. To predict which types of Liver disease affected for patients using CBR. He also proposed to determine whether patients suffer from liver disease or not using case-based reasoning, artificial neural networks and analytic hierarchy methods. They also predict which types of liver disease the human body suffers from.

The research employs a comprehensive methodology, including data collection, model development, and rigorous testing, to investigate the effectiveness of ML algorithms in healthcare settings [11]. The results demonstrate significant improvements in diagnostic accuracy, treatment personalization, and predictive analytics, evidenced through quantitative data presented in graphs and tables.

The authors of this study [12] offer a model for the purpose of making reliable predictions about the onset of foot ulcers. Model training, feature extraction, and preprocessing are all steps in a sequential process. Using mask-based segmentation, preprocessing improves picture quality and removes noise from the scanned raw RGB images. Training an ELM-PSO model, which outperforms traditional ELM and PSO algorithms, requires careful management of features and uses GLCM for feature extraction. The results show a substantial increase in precision, reaching a mark of 97.15%.

The insights garnered from this research are intended to be instrumental for healthcare professionals seeking to adapt to the changing landscape, policymakers shaping the regulatory framework, and researchers driving innovation [13]. Ultimately, this research serves as a timely and comprehensive resource, shedding light on the future trajectory of healthcare professions in the face of ongoing technological transformations and contributing to informed decision-making in the area of healthcare [14]. his methodology involves training AI models with extensive datasets of X-ray and MRI images, incorporating feature extraction and pattern recognition techniques. The results demonstrate a marked improvement in accuracy and speed over traditional biometric systems [15].

Proposed Model

DATA COLLECTION

The data collection process for the study on liver diseases involved several key components:

DATA SET: The primary dataset used in this research is the Indian Liver Patient Data (ILPD), which includes information from 583 individuals diagnosed with liver disorders. This dataset was sourced from reputable organizations, including the Directorate of Non-Medical Fields of Science and Engineering, the National Science

Foundation, and the UCI Machine Learning Repository. This ensures that the data is reliable and well-documented.

DEMOGRAPHIC INFORMATION: The study emphasizes the importance of demographic factors such as age and gender in classifying liver diseases. By analyzing these factors, the researchers aim to determine the likelihood of an individual having liver disease based on their demographic profile.

LIVER FUNCTION TEST: The classification of liver illnesses is based on various liver function test criteria. Key parameters evaluated include:

The biochemical indicators include total bilirubin and direct bilirubin, which measure the amount of bile pigment in the blood i,e a key marker for liver function. High levels of bilirubin often suggest liver damage or bile duct obstruction. Enzymatic tests such as SGPT (alanine aminotransferase) and SGOT (aspartate aminotransferase) assess liver cell damage, with elevated values indicating hepatocellular injury. Alkaline phosphatase (Alkphos), another enzyme, rises in conditions like bile duct obstruction or liver cirrhosis. Total protein and albumin levels are also measured, as they reflect the liver's ability to synthesize proteins; decreased levels may indicate chronic liver dysfunction. The albumin-to-globulin (A/G) ratio further helps differentiate between different types of liver disorders. This dataset is typically accompanied by a diagnosis label, indicating whether or not the patient has liver disease, making it highly suitable for classification tasks in machine learning. It provides a rich source for medical analysis, enabling the development of predictive models, statistical studies, and visual explorations to identify patterns and risk factors associated with liver diseases.

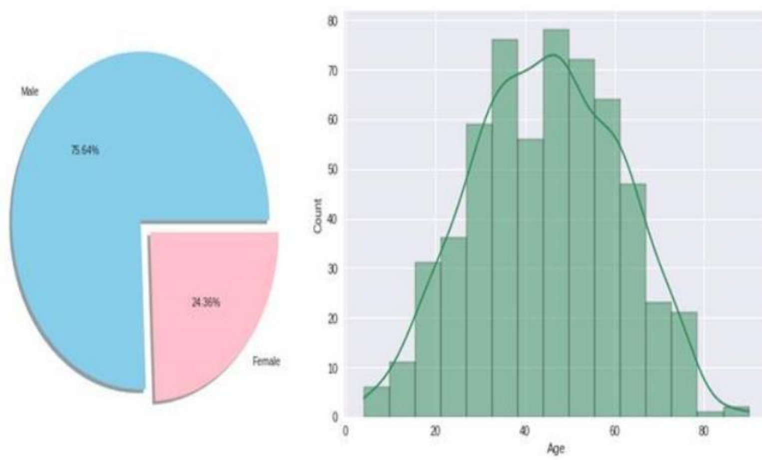

Fig.3. Patient gender count (Left), Grouping by age wise (Right).

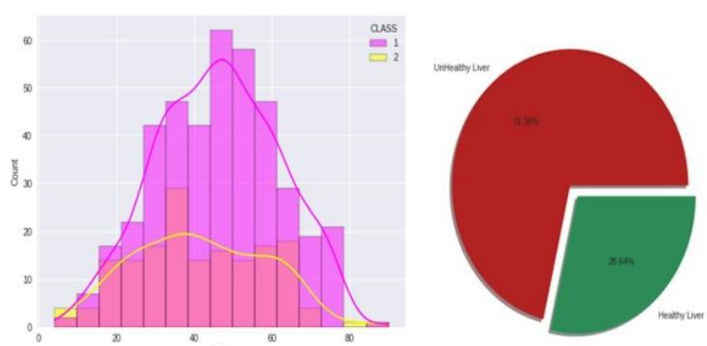

Fig.4. Classification of diseased people based on age (Left), Healthy and Unhealthy liver ratio (Right).

DATA PROCESSING

Data processing is a crucial step in the development of any machine learning model, especially in the healthcare domain where data quality directly impacts prediction performance. In this project, the Indian Liver Patient Dataset (ILPD) was used, which consists of 583 records and 10 features including demographic and biochemical parameters such as age, gender, total bilirubin, direct bilirubin, alkaline phosphatase, alanine aminotransferase (SGPT), aspartate aminotransferase (SGOT), total proteins, albumin, and albumin-to-globulin ratio. The target variable indicates whether a patient has liver disease or not.

DATA CLEANING

Data Cleaning is an essential step in preparing the dataset for machine learning modeling, as it directly influences the accuracy and performance of the predictive models. In this project, data cleaning involved identifying and handling missing values, detecting outliers, and ensuring consistency in data formats. The Indian Liver Patient Dataset contained some missing entries, particularly in the "Albumin" and "Albumin and Globulin Ratio" attributes. These were addressed using mean imputation which replaces missing values with the average value of the respective feature. This approach helps preserve the statistical properties of the dataset without introducing significant bias. Additionally, outliers were detected using visualization techniques such as boxplots and statistical methods like z-score analysis. Outliers, which can distort model learning, were either removed or treated using capping techniques to bring them within a reasonable range. Duplicate records, if any, were also removed to avoid redundancy. This cleaning process ensured that the data was accurate, complete, and ready for further preprocessing and model training.

DATA STANDARDIZATION

Data standardization converts data into a standard format that computers can read and understand. This is important because it allows different systems to share and efficiently use data. Without data standardization, it would not be effortless for different approaches to communicate and exchange information. Data standardization is also essential for preserving data quality. When data is standardized, it is much easier to detect errors and ensure that it is accurate. This is essential for making sure that decision-makers have access to accurate and reliable information.

MULTI LAYER PERCEPTRON NEURAL NETWORK

A Multilayer Perceptron (MLP) is a type of artificial neural network that consists of multiple layers of neurons, making it a powerful tool for handling complex patterns and relationships in data. It is composed of three main types of layers: the input layer, one or more hidden layers, and the output layer. Each neuron in a layer is connected to neurons in the next layer through weighted connections, and these connections are adjusted during training to optimize the network's performance. MLP operates using a feedforward architecture, meaning data flows from the input layer to the output layer without looping back. Each neuron applies a weighted sum of inputs, followed by an activation function (such as ReLU, sigmoid, or tanh) to introduce non-linearity, enabling MLP to learn complex decision boundaries.

Results & Analysis

Evaluation metrics are essential tools used to assess the performance and accuracy of machine learning models and algorithms. These metrics provide quantitative measures that enable researchers and practitioners to evaluate the effectiveness of their methods and make informed decisions about model selection and optimization. Moreover, the choice of evaluation metrics depends on the nature of the problem being addressed and the desired outcome. By utilizing a combination of evaluation metrics, practitioners can gain comprehensive insights into the overall performance of their models and make informed decisions regarding their deployment and optimization strategies. These Evaluation metrics play a crucial role in not only validating the performance of machine learning models but also in comparing different models and algorithms. They help in identifying the strengths and weaknesses of a model, guiding the refinement process for better outcomes. Common evaluation metrics include Accuracy, Precision, Recall, F1 Score and Specificity Each metric serves a specific purpose in evaluating different aspects of model performance.

Class balance along with anticipated outcomes are just two of the many factors that go into choosing the optimal metrics for assessing a classifier's performance in a specific set of data in classification challenges. A classifier

may be evaluated on one performance parameter while being unmeasured by the others, and vice versa. As a result, the generic assessment of performance of the classifier lacks a defined, unified metric. This study uses a number of metrics, including F1 score, accuracy, precision, recall, and recall, to assess how well models perform. The subsequent four categories are where these metrics are derived from: True Positives (TP): instances in which both the model prediction and the actual class of the occurrence were 1 (True). False Positives (FP) are situations in which the model predicts a value of 1 (True), but the actual class of the occurrence was 0 (False). True Negatives (TN): an instance in which both the model prediction and the true class of the occurrence were 0 (False). False Negatives (FN) are situations in which the model predicts 0 (False) but the true class of the occurrence was 1 (True).
Accuracy– The mean amount of accurate predictions is used to characterize the accuracy measure. This isn't quite as strong, though, given the imbalanced sample.

$$= \frac{+}{+ \; + \; +} \qquad (1)$$

Precision, also known as positive predictive value, gauges the capacity of a model to pinpoint the right examples for every class. For multi-class classification with unbalanced datasets, this is a powerful matrix.

$$= \frac{}{+} \qquad (2)$$

Recall – This metric assesses how well a model detects the true positive among all instances of true positives.

$$= \frac{}{+} \qquad (3)$$

F1-score – referred to as an F-measure or balanced F-score It might be characterized as a recall as well as precision weighted average.

$$1 = \frac{2 * Pcso * ca}{+} \qquad (4)$$

Fig.5. Actual vs Predicted by Correlation Heat map

The correlation heatmap presented in the slide highlights the relationships between various numerical features in the dataset. Features such as Albumin, Total Bilirubin, and SGPT/SGOT levels were analyzed to understand their interdependencies. Strong positive or negative correlations can guide feature selection and engineering by identifying multicollinearity or key influencing factors related to liver health.

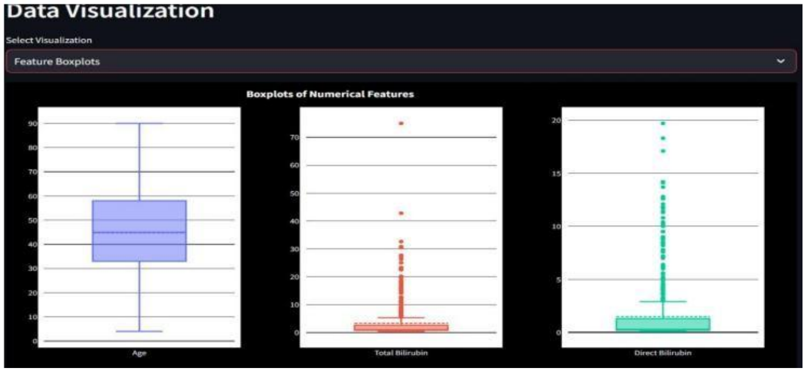

Fig.6. Actual vs Predicted by Feature Boxplots

Box plots were generated for critical numerical features, including Age, Total Bilirubin, and Direct Bilirubin. These visualizations help detect outliers, skewness, and distribution spread. For instance, both Total and Direct Bilirubin display significant outliers, indicating a wide range of values likely due to varying liver conditions. Age also shows variability, suggesting the disease is not confined to a narrow age group.

A variety of machine learning algorithms were evaluated based on multiple performance metrics such as Accuracy, Precision, Recall, F1 Score, and Specificity. The results reveal: The Voting Classifier achieved the highest accuracy (0.6837) and F1 Score (0.6981), indicating that ensemble methods combining multiple models provide better predictive performance. The XGBoost model also performed well, showing a good balance between precision and recall. Models like Naive Bayes and Decision Tree had lower performance, possibly due to oversimplification or overfitting. The ANN Classifier showed competitive results, emphasizing the potential of neural networks in handling medical datasets. This comparative analysis validates the use of ensemble and advanced models for improving predictive accuracy and robustness in liver disease classification.

MODEL	ACCURACY	PRECISION	RECALL	F1 SCORE	SPECIFICITY
Logistic Regression	0.6581196581	0.7741543703	0.6581196581	0.6727408912	0.578313253
Naive Bayes	0.5811965812	0.67897754773	0.5811965812	0.5867099737	0.4337349398
Decision Tree	0.5982905983	0.7788441188	0.5982905983	0.0.6079611072	0.4698795181
SVM	0.641025641	0.779696494	0.641025641	0.6546231546	0.5421686747
Random Forest	0.6495726496	0.7396134614	0.6495726496	0.6656068454	0.6024096386
K-Nearest Neighbor	0.6581196581	0.6402367919	0.581196581	0.6475400902	0.7951807229
XGBoost	0.6666666667	0.6465020576	0.66666666667	0.6542847216	0.8072289157
ANN Classifier	0.6581196581	0.627676681841	0.6581196581	0.6383597246	0.8192771084
Voting Classifier	0.6837606838	0.7552397423	0.6837606838	0.6981697282	0.6506024096

Table.1. Comparison Table

This GUI application predicts liver disease using machine learning techniques. It utilizes a Multi-Layer Perceptron (MLP) and Voting Classifier ensemble method. The application collects user input for various liver disease indicators. These inputs are then processed and fed into the trained models. The MLP model uses multiple layers to learn complex relationships between inputs. The Voting Classifier combines predictions from multiple models for improved accuracy. The application displays the predicted outcome, indicating the likelihood of liver disease. It also provides information on the model's performance metrics.

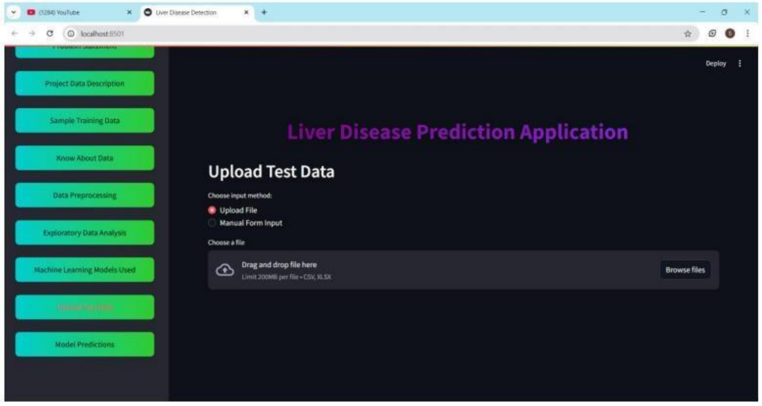

Fig.7. GUI Application for liver disease prediction

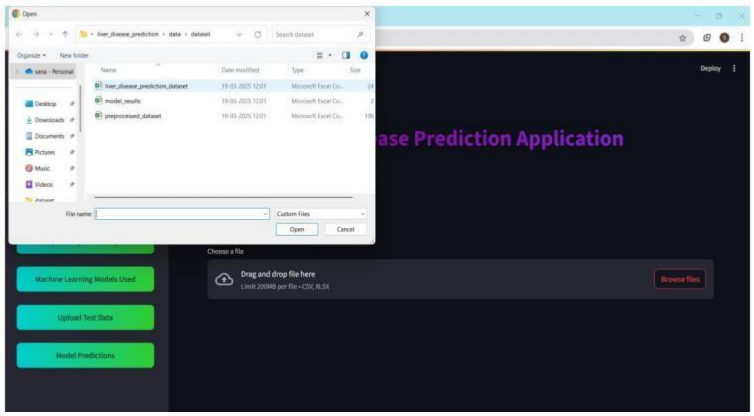

Fig-10: Loading liver disease Dataset into application

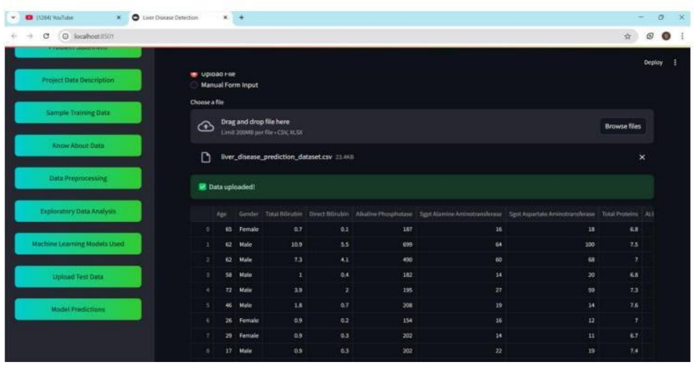

Fig-11: Displaying the dataset

Fig-15: Estimation of Test Data

Conclusion

The death rate due to liver disease has been rising since 1980, primarily because symptoms often go unnoticed until the condition becomes severe. When symptoms appear, they may include jaundice, bloating, and stomach pain, but people tend to ignore them, worsening the disease until it becomes fatal. While advanced imaging techniques exist, some liver conditions remain undetectable through scans. This study explores the early detection of liver diseases using blood-based liver function tests. After testing multiple machine learning and deep learning models—SVM, KNN, MLP, and Hard Voting Classifier (HVC)—results showed that the Hard Voting Classifier performed best, achieving an accuracy of 0.78, specificity of 0.94, F-score of 0.87, precision of 0.80, and recall of 0.94. The confusion matrix confirmed that the Voting Classifier made more accurate predictions than other models, making it the most effective for liver disease detection. Future work will focus on improving the Hard Voting Classifier’s performance through feature selection algorithms and optimization strategies for identifying other diseases.

Future Scope

The future scope of the project "Liver Disease Prediction using Multilayer Perceptron Neural Network and Voting Classifier Ensemble" is vast and promising. Here are some potential areas for expansion and improvement, Integration with Electronic Health Records (EHRs) for seamless data exchange. Expansion to predict other diseases, such as diabetes or cardiovascular disease. Incorporating additional features, like genetic data or medical imaging. Real-time prediction and alert system for timely interventions. Cloud-based deployment for scalability and accessibility. The project can evolve and improve, contributing to better healthcare outcomes and disease prediction strategies. Future developments can enhance accuracy, accessibility, and adoption. The future scope of this project includes improving feature selection for better accuracy, integrating medical imaging for enhanced detection, and developing a real-time prediction system via web or mobile applications. Optimization techniques like hyper parameter tuning can further refine the Hard Voting Classifier’s performance.

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