VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY
An Autonomous Institute Affiliated to University of Mumbai
Department of Computer Engineering

Project Report on

Liver Cirrhosis Prediction System

In partial fulfillment of the Fourth Year, Bachelor of Engineering (B.E.) Degree in Computer Engineering at the University of Mumbai Academic Year 2023-24

Submitted by
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(2023-24)

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Certificate

This is to certify that ***Vidhi Chijwani (D17B ,18), Ritesh Tahilramani (D17B ,66),Navin Idnani (D17C ,22),Nikita Narwani (D17C,39***) of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on "***Liver Cirrhosis Prediction System***" as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor ***Dr. Rohini Temkar*** in the year 2023-24 .

This thesis/dissertation/project report entitled ***Liver Cirrhosis Prediction System*** by ***Vidhi Chijwani,Ritesh Tahilramani,Navin Idnani,Nikita Narwani*** is approved for the degree of ***B.E. Computer Engineering***.

Programme Outcomes	Grade
PO1,PO2,PO3,PO4,PO5,PO6,PO7, PO8, PO9, PO10, PO11, PO12 PSO1, PSO2	

Date:

Project Guide:

Project Report Approval
For
B. E (Computer Engineering)

This thesis/dissertation/project report entitled ***Liver Cirrhosis Prediction System*** by ***Vidhi Chijwani,Ritesh Tahilramani,Navin Idnani,Nikita Narwani*** is approved for the degree of ***B.E. Computer Engineering***.

Internal Examiner

External Examiner

Head of the Department

Principal

Date:
Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement at several times.

Computer Engineering Department
COURSE OUTCOMES FOR B.E PROJECT

Learners will be to,

Course Outcome	**Description of the Course Outcome**
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilized.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one's competency.
CO 11	Able to develop professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

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Abstract

Liver cirrhosis is a critical medical condition with potentially life-threatening consequences if not diagnosed and managed timely. In this project, we aimed to develop an effective liver cirrhosis prediction system utilizing machine learning algorithms. The system utilizes a comprehensive dataset encompassing various clinical and demographic features to train and evaluate predictive models. We employed three prominent machine learning algorithms, namely XGBoost, Random Forest, and Support Vector Machine (SVM), to predict the presence of liver cirrhosis based on patient data. Our study focused on evaluating the predictive performance of these algorithms using rigorous testing procedures. Performance evaluation metrics such as accuracy, precision, recall, and specificity were employed to assess the efficacy of each algorithm in predicting liver cirrhosis across diverse test case scenarios. Results demonstrated that XGBoost exhibited superior predictive capabilities with an accuracy of 90%, followed by Random Forest at 73%, and SVM at 60%. Challenges and limitations such as data quality issues, feature selection bias, and limited available datasets were also identified during the comparison with existing systems. These findings underscore the importance of addressing data quality concerns, refining feature selection methodologies, and expanding available datasets to enhance the accuracy and reliability of liver cirrhosis prediction systems. In conclusion, our study highlights the potential of machine learning algorithms in improving liver cirrhosis prediction and underscores the need for continued research and development efforts to overcome existing challenges and optimize predictive models for clinical applications. By leveraging advanced machine learning techniques, we aim to contribute to the advancement of medical diagnosis and prognosis in the context of liver cirrhosis.

Chapter 1: Introduction

1.1 Introduction

The liver is one of the body's most crucial organs.Liver should do their proper functions to maintain the body healthy and fit.Liver cirrhosis is a progressive medical condition characterized by the gradual deterioration and scarring of liver tissue, which severely impairs its vital functions.Our primary goal is to develop a Liver Cirrhosis Detection System, leveraging advanced machine learning techniques, to enable early detection and diagnosis of this debilitating condition.

1.2 Motivation

The motivation for liver cirrhosis prediction systems lies in the urgent need to improve patient care and optimize healthcare resources in the face of chronic liver disease's significant morbidity and mortality. These systems offer a standardized approach to assess disease severity, predict outcomes, and tailor treatment strategies for individual patients. By accurately stratifying patients based on their predicted risk, healthcare providers can optimize resource allocation, enhance healthcare efficiency, and ultimately improve patient outcomes. Additionally, liver cirrhosis prediction systems contribute to advancing scientific knowledge by facilitating clinical research and evidence-based practice in hepatology.

1.3 Problem Definition

Liver cirrhosis, characterized by gradual liver tissue scarring and functional decline, poses a critical healthcare problem.Late diagnosis also inflates healthcare costs and exerts a substantial burden on healthcare systems. The adverse impact on patients' quality of life underscores the urgent need for early detection.To address these complex issues, our project aims to develop a Liver Cirrhosis Detection System, harnessing advanced machine learning and comprehensive patient data analysis to enable early identification and intervention. This initiative strives for improved patient outcomes, cost-effective healthcare, and a positive impact on public health.

1.4 Existing Systems

Several liver cirrhosis prediction systems have been developed to assess the severity of liver disease and predict outcomes in patients with chronic liver conditions. Among these are the Child-Pugh Score, which evaluates clinical parameters including ascites, hepatic encephalopathy, serum bilirubin, albumin levels, and prothrombin time to categorize patients into different severity classes. The Model for End-Stage Liver Disease (MELD) and its modification MELD-Na incorporate laboratory values such as bilirubin, creatinine, INR, and sodium to predict short-term mortality and guide liver transplant allocation. Non-invasive scoring systems like the FIB-4 Score and APRI Score utilize routine laboratory tests such as AST, ALT, and platelet count to assess liver fibrosis and predict the presence of cirrhosis, particularly in patients with hepatitis C. Additionally, consensus statements such as Baveno VI provide guidelines for managing patients with advanced chronic liver disease, aiming to identify those who may not require invasive screening procedures like esophagogastroduodenoscopy for esophageal varices. While dedicated mobile applications for these prediction systems may not be widespread, healthcare professionals often utilize general medical calculator apps or liver disease management tools to apply these scoring systems in clinical practice.

1.5 Lacuna of the existing systems

Liver cirrhosis prediction models have made significant advancements in recent years, but there are still some lacuna or gaps in these models that researchers and healthcare professionals are working to address. Here are some notable gaps or challenges in existing liver cirrhosis prediction models:

1. Data Availability and Quality
2. External Validation
3. Ethical and Privacy Concerns

1.6 Relevance of the Project

Liver cirrhosis prediction systems hold significant relevance in clinical practice and patient care. These systems serve as invaluable tools for healthcare professionals in several critical aspects of managing chronic liver disease. Firstly, they enable risk stratification, allowing providers to categorize patients based on the severity of their liver disease. This stratification informs treatment decisions and interventions, ensuring appropriate care pathways for each patient. Moreover, these prediction systems offer prognostic insights, aiding in the assessment of disease progression, complications, and survival probabilities. Such information not only guides treatment strategies but also facilitates patient education and counseling, empowering individuals to actively engage in their healthcare journey. Additionally, liver cirrhosis prediction systems contribute to resource allocation by identifying patients at higher risk of adverse outcomes, ensuring optimal utilization of healthcare resources and timely interventions. Furthermore, these systems play a vital role in research and quality improvement endeavors, facilitating the evaluation of interventions, comparison of outcomes, and identification of areas for enhancing healthcare delivery and patient outcomes. In essence, liver cirrhosis prediction systems are indispensable tools that optimize patient care, improve clinical outcomes, and enhance the efficiency of healthcare delivery in managing chronic liver disease.

Chapter 2: Literature Survey

A. Brief Overview of Literature Survey

Through our review, several key themes emerge. The utilization of machine learning algorithms for liver disease prediction is prevalent, indicating a promising avenue for early detection and prevention of liver diseases to improve patient outcomes. However, the varying performance of machine learning models, coupled with concerns regarding the choice of evaluation metrics and methods, underscores the complexity of this field. Ethical considerations surrounding patient data usage and model generalizability further highlight the need for careful consideration in research endeavors.Researchers employ a variety of methodologies and approaches, including decision trees, classification algorithms (e.g., Logistic Regression, K-Nearest Neighbour, Support Vector Machines), and deep learning algorithms (e.g., Convolutional Neural Networks). These methods leverage diverse datasets encompassing clinical, laboratory, and patient history data.There is a notable trend in the utilization of machine learning methods, particularly deep learning algorithms, for liver disease prediction. Research efforts are increasingly focused on improving early-stage detection and diagnosis, aiming to enhance patient outcomes and quality of life.Despite advancements, there are gaps in the literature, particularly regarding the choice of evaluation metrics and methods. Inappropriate metrics selection may lead to misleading conclusions, highlighting the need for standardization in evaluation methodologies. Additionally, there are concerns about model generalizability and ethical data usage, warranting further investigation.Our study aims to address the identified gaps and challenges in the literature. By employing rigorous evaluation methodologies and considering ethical implications, we seek to develop robust machine learning models for liver disease prediction. Our research contributes to advancing knowledge in this field and may ultimately lead to improved diagnostic accuracy and patient outcomes.

In summary, our literature review provides valuable insights into the current state of liver disease prediction using machine learning algorithms.

By understanding the existing advancements, challenges, and gaps, we are better equipped to guide our own research efforts. Our study aims to address these challenges and contribute to the advancement of knowledge in liver disease prediction, ultimately benefiting patients and healthcare practitioners alike.

B. Related Works

1. Evaluation-based Approaches for Liver Disease Prediction using Machine Learning Algorithms: Geetha and Arunachalam (2021) explored various machine learning algorithms for predicting liver diseases, aiming to enhance early detection and prevention strategies. Their study compared the performance of different algorithms and emphasized the importance of selecting appropriate evaluation metrics to ensure reliable results.

2. Early-Stage Detection of Liver Disease Using Decision Tree: Dutta, Chandra, and Kumar (2022) proposed a decision tree-based approach for early-stage detection of liver disease. By leveraging clinical, laboratory, and patient history data, their study focused on developing a simple yet effective model for accurate diagnosis, highlighting the interpretability and ease of implementation of decision trees in medical settings.

3. Prediction of Liver Disease using Classification Algorithms: Thirunavukkarasu et al. (2018) investigated the prediction of liver disorders using various classification algorithms, including logistic regression, K-nearest neighbor, and support vector machines. Their research aimed to develop predictive models based on clinical data to assist in the early diagnosis and management of liver diseases.

4. Intelligent Model for Liver Disease Prediction: Ghazal et al. (2022) presented an intelligent model for liver disease prediction, achieving a high accuracy rate

of 88.4%. Their study demonstrated the potential of machine learning algorithms to outperform traditional diagnostic methods, emphasizing the importance of leveraging advanced technologies for improved healthcare outcomes.

5. Prediction of Chronic Liver Disease Patients using Integrated Feature Extraction: Amin et al. (2022) proposed an integrated feature extraction approach for predicting chronic liver disease patients using machine learning algorithms. By focusing on feature selection and model refinement, their study aimed to enhance prediction accuracy and assist in the classification of chronic liver disease patients for targeted interventions.

6. Survey on Liver Disease Prediction using Convolutional Neural Network: Kaviya and Vijayabhanu (2021) conducted a survey on liver disease prediction using convolutional neural networks (CNNs), exploring the potential of deep learning algorithms in achieving more accurate results compared to traditional classification methods. Their research highlighted the growing interest in leveraging deep learning techniques for improved healthcare diagnostics.

7. Diagnosis of Liver Diseases using Machine Learning: Sontakke et al. (2017) focused on the diagnosis of liver diseases using machine learning techniques, emphasizing the challenges associated with dataset selection and the importance of considering various patient parameters in disease diagnosis. Their study aimed to contribute to the development of reliable diagnostic tools for liver diseases.

2.1 Research Papers Referred

1. Geetha, C., & Arunachalam, A. (2021). Evaluation based Approaches for Liver Disease Prediction using Machine Learning Algorithms. 2021 International Conference on Computer Communication and Informatics (ICCCI).
2. Dutta, K., Chandra, S., & Kumar, M. (2022). Early-Stage Detection of Liver Disease Using Decision Tree. Advances in Data and Information Sciences.
3. Thirunavukkarasu, K., Singh, A. S., Irfan, M., & Chowdhury, A. (2018). Prediction of Liver Disease using Classification Algorithms. 4th International Conference on Computing, Communication and Automation (ICCCA).
4. Ghazal, T. M., Ur Rehman, A., Saleem, M., Ahmad, M., Ahmad, S. (2022). 2022 International Conference on Business Analytics for Technology and Security (ICBATS).
5. Amin, R., Yasmin, R., Ruhi, S., Rahman, M. H., & Rahman, M. S. (2022). Prediction of chronic liver disease patients using integrated projection-based statistical feature extraction with machine learning algorithms. Informatics in Medicine Unlocked.
6. Kaviya, & Vijayabhanu, R. (2021). Prediction of Liver Disease using Convolutional Neural Network- A Survey. International Research Journal of Engineering and Technology (IRJET).
7. Sontakke, S., Lohokare, J., Dani, R. (2017). Diagnosis of Liver Diseases using Machine Learning. International Conference on Emerging Trends & Innovation in ICT (ICEI).

a. Abstract of the research paper

This study explores the application of machine learning algorithms for liver disease prediction, aiming to enhance early detection and prevention strategies. Various methodologies, including decision trees, classification algorithms, and deep learning models, are investigated across nine research papers to develop predictive models based on clinical data.

Key findings indicate promising results in terms of prediction accuracy, with some studies achieving high rates of success. However, concerns regarding model generalizability, appropriate evaluation metrics, and ethical considerations surrounding patient data usage persist. The research contributes to the advancement of knowledge in liver disease prediction and underscores the importance of leveraging innovative methodologies and comprehensive datasets to improve patient outcomes in healthcare settings.

b. Inference drawn

Analyzing the collective body of research represented we have valuable insights into the multifaceted landscape of liver disease prediction using machine learning algorithms. Geetha and Arunachalam (2021) present an overarching framework for evaluating machine learning approaches in liver disease prediction, emphasizing the critical role of appropriate evaluation metrics. Their work serves as a foundational pillar, setting the stage for subsequent studies to build upon. Dutta, Chandra, and Kumar (2022) delve deeper into the realm of early-stage detection, showcasing the potential of decision tree-based methodologies. This approach offers a practical and interpretable solution, essential for swift clinical intervention and treatment planning. Thirunavukkarasu et al. (2018) expand the horizon by exploring classification algorithms for liver disease prediction, demonstrating the versatility of machine learning in medical diagnostics. Their study underscores the importance of leveraging diverse algorithms to capture the intricate patterns within clinical data. Moving forward, Ghazal et al. (2022) present an innovative model at the intersection of business analytics and healthcare technology. Their work highlights the transformative potential of machine learning in enhancing diagnostic accuracy and optimizing healthcare delivery systems. Amin et al. (2022) contribute significantly to the field by introducing an integrated feature extraction approach tailored specifically for predicting chronic liver disease patients.

By integrating statistical feature extraction techniques with machine learning algorithms, their study showcases a novel methodology for improving predictive performance in complex medical scenarios. Meanwhile, Kaviya and Vijayabhanu (2021) shed light on the burgeoning field of convolutional neural networks (CNNs) in liver disease prediction. Their survey provides a comprehensive overview of the current landscape, paving the way for future advancements in deep learning methodologies.Sontakke, Lohokare, and Dani (2017) explore the diagnostic capabilities of machine learning in liver diseases, emphasizing the importance of dataset selection and parameter optimization. Their research underscores the need for robust and reliable diagnostic tools to aid healthcare professionals in accurate disease identification.

Collectively, these studies represent a diverse tapestry of research endeavors, each contributing a unique perspective to the broader discourse on liver disease prediction. Through collaborative efforts and interdisciplinary approaches, researchers aim to unlock new frontiers in medical diagnostics and improve patient outcomes in the realm of liver disease management.

2.3. Inference drawn

The patents related to liver cirrhosis prediction using machine learning algorithms underscore a significant advancement in medical diagnostics and proactive healthcare management. These innovations introduce novel methods and systems designed to leverage machine learning techniques for predicting the risk of liver cirrhosis development. By integrating diverse datasets encompassing clinical, laboratory, and demographic information, these systems train predictive models to estimate the likelihood of liver cirrhosis with enhanced accuracy. Through the utilization of advanced algorithms, these methods aim to improve the diagnostic accuracy and reliability of liver cirrhosis assessments, offering healthcare professionals valuable tools for early detection and intervention.

Central to the patents is the emphasis on early detection and intervention in liver cirrhosis cases, aligning with the overarching goal of proactive healthcare management. Machine learning-based systems facilitate the identification of individuals at risk of developing liver cirrhosis at an early stage, enabling timely intervention and preventive measures to mitigate disease progression. By providing clinicians with actionable insights into liver health, these innovations have the potential to transform healthcare delivery, optimizing patient outcomes and resource utilization in the context of liver disease management.

Moreover, these patents signify the translational potential of machine learning in clinical practice, offering scalable solutions for liver cirrhosis prediction and patient management. With the ability to analyze complex datasets and generate predictive models, these systems empower healthcare professionals to make informed decisions regarding patient care. By facilitating early detection, personalized intervention, and continuous monitoring, these innovations pave the way for proactive healthcare strategies aimed at improving liver health outcomes and enhancing overall patient well-being.

2.4 Comparison with the existing system

1. Traditional Diagnostic Methods:

Traditional diagnostic methods for liver cirrhosis typically involve the use of liver function tests, imaging studies (such as ultrasound or CT scans), and clinical assessments. These methods often rely on individual biomarkers or imaging findings to assess liver health and detect signs of cirrhosis. While these methods have been the standard of care for many years, they may have limitations in terms of diagnostic accuracy, especially in early stages of the disease. They may also lack the ability to integrate and analyze diverse patient data comprehensively.

2. Conventional Machine Learning Approaches:

Conventional machine learning approaches for liver cirrhosis prediction involve the use of algorithms such as logistic regression, decision trees, and support vector machines. These approaches typically rely on predefined features extracted from patient data, such as clinical parameters and laboratory results. While these methods have shown promise in improving diagnostic accuracy compared to traditional methods, they may still have limitations in capturing complex relationships within the data and adapting to changing patient profiles over time.

3. Deep Learning-Based Systems:

Deep learning-based systems represent a significant advancement in liver cirrhosis prediction compared to traditional diagnostic methods and conventional machine learning approaches. These systems utilize neural networks with multiple layers to automatically learn hierarchical representations of patient data directly from raw inputs, such as medical images or genetic data. By leveraging the power of deep learning, these systems can capture complex patterns and relationships within the data, leading to enhanced diagnostic accuracy and predictive performance. They also offer the flexibility to integrate diverse datasets and adapt their predictive models over time, making them well-suited for personalized healthcare applications.

In comparison to traditional diagnostic methods, deep learning-based systems offer improved diagnostic accuracy, especially in early stages of liver cirrhosis, and the ability to integrate diverse patient data comprehensively. Compared to conventional machine learning approaches, deep learning-based systems excel in capturing complex relationships within the data and adapting to changing patient profiles, leading to more accurate and reliable predictions. Overall, deep learning-based systems represent a significant advancement in liver cirrhosis prediction and have the potential to revolutionize diagnostic practices in hepatology.

Chapter 3: Requirement Gathering for the Proposed System

3.1 Introduction to requirement gathering

This chapter explores the resources used, user needs analysis, functional and non-functional requirements, software and hardware, and their analysis.

There are six steps in the requirements gathering process:

- Determine the pertinent parties involved
- Set project objectives and goals
- Gather requirements from parties involved
- Record the requirements
- Verify the requirements
- Order the requirements

USE CASE	**DESCRIPTION**
Register and Login	Healthcare professionals, such as doctors and researchers, as well as administrators, register and log in to the system.
Input Patient Data	Healthcare professionals input patient data including medical history, lab results, demographics, and symptoms.
Predict Cirrhosis Risk	The system predicts the risk of liver cirrhosis based on the input patient data using machine learning algorithms.
Display Prediction Results	The prediction results, including the likelihood of cirrhosis and associated risk factors, are displayed to the healthcare professional
Recommend Diagnostic Tests	The system recommends specific diagnostic tests or procedures based on the predicted risk and patient data.
Monitor Patient Progress	Healthcare professionals can monitor patient progress over time, track changes in risk factors, and adjust treatment plans accordingly.

Send Notifications	The system sends notifications or alerts to healthcare professionals regarding significant changes in patient.
View Patient History	Healthcare professionals can view the historical data and previous predictions for individual patients
Update Patient Records	Healthcare professionals can update patient records with new data or information as it becomes available.
Generate Reports	The system generates comprehensive reports summarizing patient risk assessments, trends, and outcomes.
Provide Decision Support	The system provides decision support tools and recommendations to assist healthcare professionals in managing patient care.

Table 3.1 Use cases

3.2 Functional Requirements

A liver cirrhosis prediction model system's functional requirements would specify what the system must be able to perform and the particular features it needs in order to satisfy its customers' needs. The liver cirrhosis prediction model system needs to meet the following functional requirements:

- **Data Integration:**The system should integrate data from various sources like EHRs, laboratory databases, imaging systems, and patient demographics databases.

- **Real-time Prediction** :The system should offer real-time prediction capabilities, enabling healthcare professionals to input patient data and receive immediate predictions of liver cirrhosis risk.

- **Security and Privacy:**The system should implement robust security measures to protect patient data from unauthorized access, disclosure, and tampering. This includes encryption, access controls, and audit trails to ensure compliance with healthcare privacy regulations.

- **User Interface:** The system should have an intuitive and user-friendly interface for healthcare professionals to interact with. The interface should allow users to input patient data, visualize prediction results, and interpret model outputs easily.

- **Integration with Healthcare Systems:** The system should integrate seamlessly with existing healthcare information systems such as EHRs and hospital

management systems. This facilitates the exchange of patient data and ensures interoperability with other clinical workflows

- **Training and Support:** The system should offer comprehensive training materials, documentation,and technical support to healthcare professionals,including user manuals and online resources,to enhance their use of prediction system for cirrhosis.

3.3 Non-Functional Requirements

The qualities that a system must possess, like performance, usability, dependability, and security, are referred to as non-functional requirements. These are the liver cirrhosis prediction model system's non-functional requirements:

1. Performance:

- During data processing, model training, and prediction, the system should react to user inputs quickly and with the least amount of latency possible.
- Even with a massive dataset, the model prediction should fall within a reasonable reaction time.

2. Usability:

- Both technical and non-technical users should be able to easily and intuitively navigate the user interface.
- For users to maximize the usage of its features, the system ought to offer comprehensive instructions and direction.

3. Compliance: In terms of healthcare data, privacy, and security, the system should abide by all applicable laws, rules, and industry standards.

4. Response Time: To ensure a seamless user experience, the system must have reasonable response times for all user activities.

3.4.Hardware, Software , Technology and tools utilized

A. Hardware Requirements:-

a. Minimum 8 GB RAM

b. Core I5 7th Gen processor

c. NVIDIA GPU

d. Disk space of 4GB

B. Software Requirements:-

1. Python
2. Matplotlib, Seaborn, Pandas, Numpy, Sklearn.
3. HTML
4. CSS
5. React

a. Flask

b. Google Colab/Jupyter Notebook

3.5 Constraints

1. Data Privacy and Security: Medical data is highly sensitive and subject to stringent privacy regulations. Developing prediction models while adhering to privacy laws and ensuring patient confidentiality is a critical constraint.

2. Data Availability and Quality: The availability of high-quality and comprehensive medical data pertaining to liver cirrhosis is crucial. Inadequate or poorly curated data can significantly affect the accuracy and dependability of prediction models.

3. Interpretability and Explainability: In the medical domain, it's vital to create prediction models that are interpretable and offer insights into the features influencing the prediction. Black-box models may not be suitable for medical professionals who need to comprehend the reasoning behind predictions.

4. Clinical Heterogeneity: Liver cirrhosis is a complex condition with diverse causes and manifestations. Integrating and analyzing data from patients with different etiologies, comorbidities, and stages of cirrhosis is challenging.

Tools:

- **Google Colab:-** Google Research produces a product called Colaboratory, or simply "Colab." With Colab, anyone can write and run any Python code through a browser, making it particularly useful for data analysis, machine learning, and teaching. Technically speaking, Colab is a hosted,Jupyter notebook service that offers free access to computer resources, including GPUs, and doesn't require any setup.

- **Visual Studio Code (Vscode):** is a simplified code editor that facilitates development tasks such as version management, task execution, and debugging. Its goal is to give developers all the tools they need for a fast code-build-debug cycle; more complicated processes are left to more feature-rich IDEs, such Visual Studio IDE.

Chapter 4: Proposed Design

4.1 Block diagram of the system

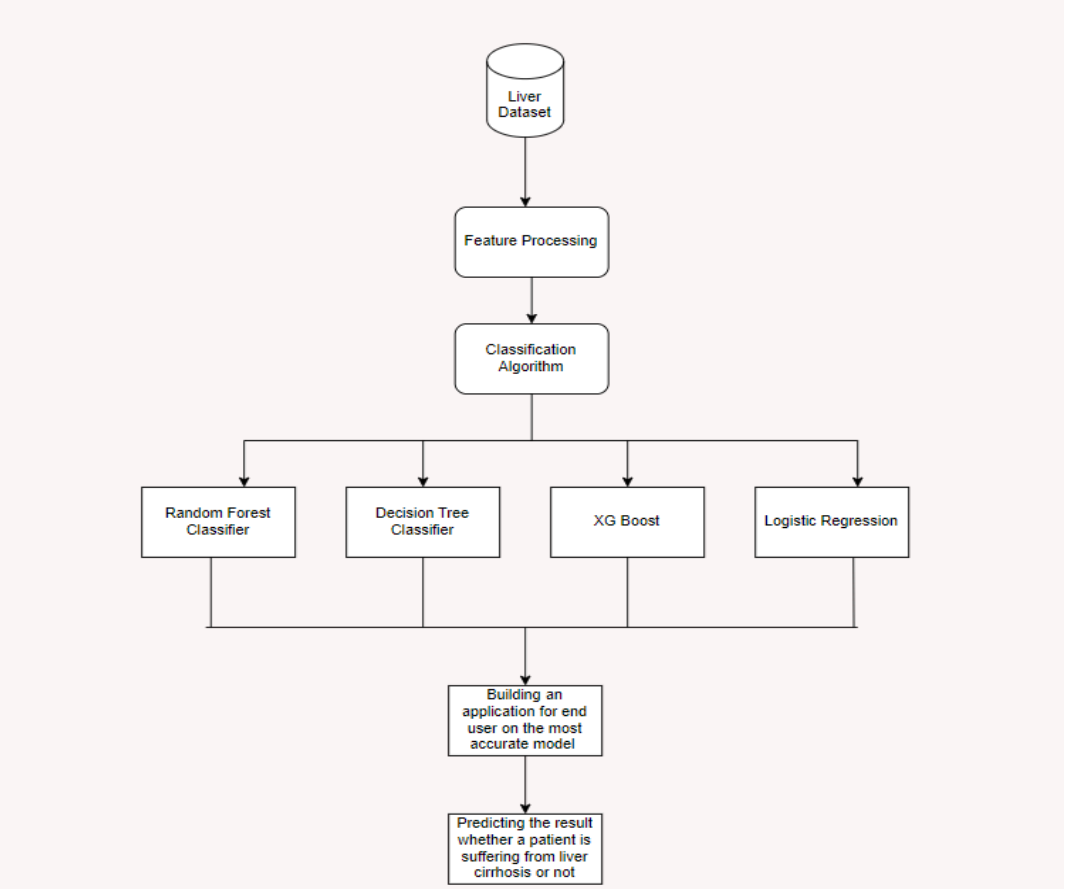


Fig 4.1 Block diagram of the proposed system

1. Data Collection : Gathering dataset from kaggle with twenty as main features; from that, we have found thirteen features only that have more importance

2. Data Preprocessing and Cleaning : This block involves tasks like dropping missing values, noise reduction, and data augmentation to prepare the dataset for training. Data cleaning ensures high-quality input for the model.

3. Model Training : Train different models such as Logistics regression, random forest classifiers,and decision tree using preprocessed data The training process involves feature extraction and model optimization.

4. Model Evaluation : Assess the model's performance using validation datasets and metrics such as accuracy, precision, recall, and F1-score. Fine-tune the model based on evaluation results.

5. Deployment : Deploying the model to production environments using flask

6. Integration with web application : Ensuring seamless integration of the Plant Disease Prediction Model with the Mobile and Web Application. Developing APIs or endpoints for communication between the application and the model.

7. Input image from user : Implement functionality in the application to allow users to submit their data for analysis. Process user input for prediction.

8. Final output to the user : Present the analysis results to users in an understandable format. Include information about the detected disease, severity, and recommended actions. Present the analysis results to users in an understandable format. Include information about the detected disease.

4.2 Modular design of the system

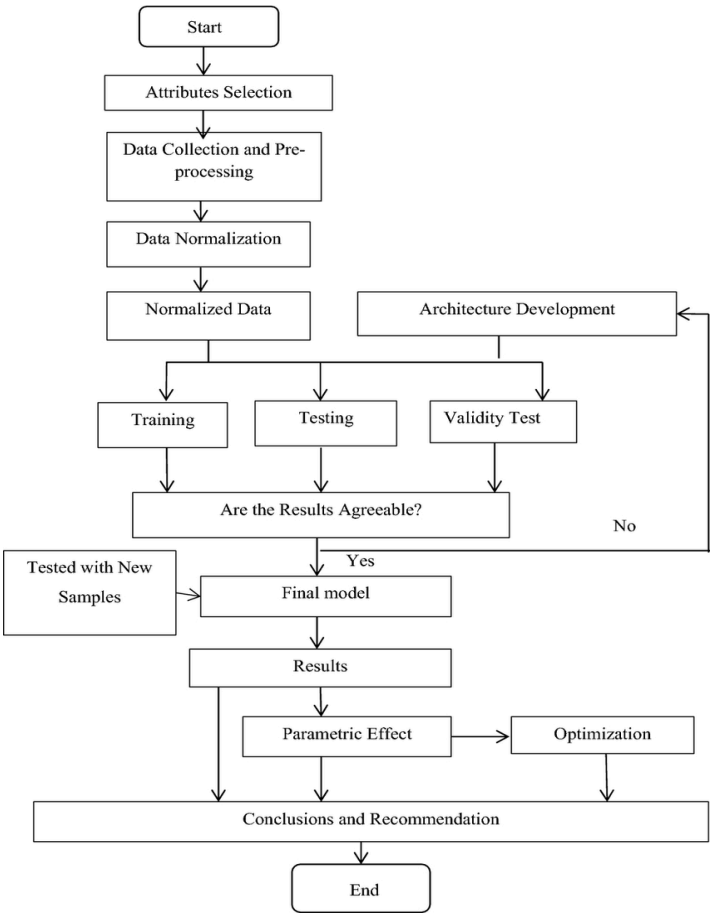


Fig 4.2 Modular diagram

4.3 Detailed Design

DFD LEVEL 0

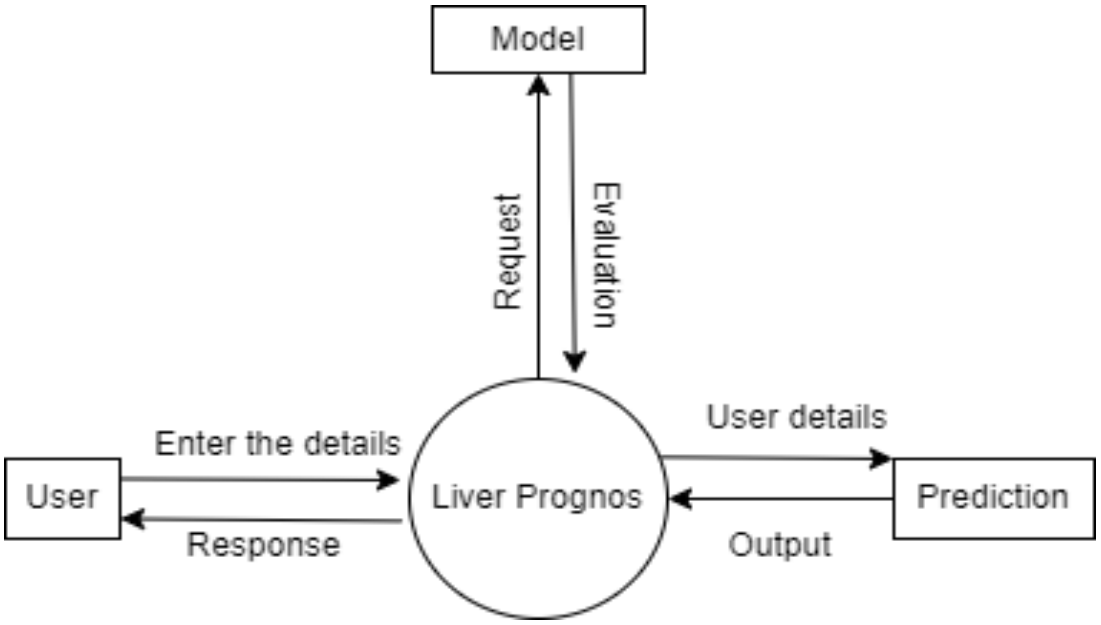


Fig 4.3.1 Level 0 Data flow Diagram

DFD LEVEL 1

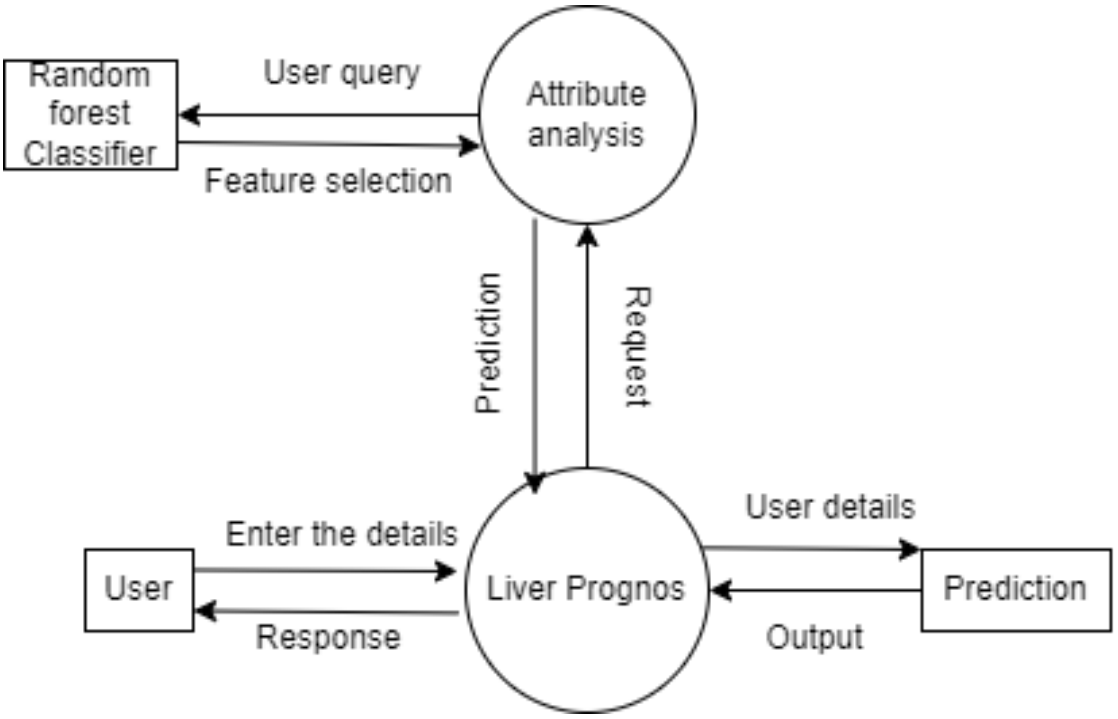


Fig 4.3.2 Level 1 Data flow Diagram

Chapter 5: Implementation of the Proposed System

5.1.Methodology employed for development:

Liver cirrhosis poses a significant public health challenge globally, necessitating the development of effective predictive systems for early detection and management. In response to this imperative, our Liver Cirrhosis Prediction System leverages advanced methodologies integrating medical knowledge, data science, and technological innovation to provide a comprehensive solution for healthcare professionals. Through a meticulous approach encompassing data collection, preprocessing, feature selection, model development, and validation, our system empowers clinicians with predictive insights to identify individuals at risk of liver cirrhosis. Furthermore, our platform fosters collaboration and knowledge exchange among medical practitioners, facilitating informed decision-making and proactive intervention strategies. With a user-centric design and robust infrastructure, our Liver Cirrhosis Prediction System stands at the forefront of combating this debilitating disease, striving towards improved patient outcomes and enhanced healthcare delivery. We have developed a comprehensive website that integrates various functionalities aimed at early detection and management of liver cirrhosis. Drawing inspiration from the methodology outlined in the sample, our platform combines elements of data collection, predictive modeling, and user interaction to provide a holistic solution for healthcare professionals and patients.

Firstly, the website facilitates data collection by allowing healthcare providers to input patient information, including relevant clinical parameters such as ascites, hepatomegaly, bilirubin levels, and other indicators associated with liver function. This data is securely stored and processed to generate predictive insights regarding the likelihood of liver cirrhosis development in individual patients.

Additionally, the platform incorporates features for predictive modeling, wherein machine learning algorithms analyze the collected data to identify patterns and risk factors indicative of liver cirrhosis. Through data preprocessing, feature selection, and model training, the system produces accurate predictions that aid healthcare professionals in making informed decisions regarding patient care and treatment strategies.

Furthermore, the website offers user interaction functionalities to enhance engagement and usability. Patients can access their personalized prediction results and corresponding recommendations through a user-friendly interface. Healthcare providers can also interact with the system to input additional patient data, track patient progress, and receive real-time alerts for high-risk cases.

Moreover, the platform includes a module for collaboration and knowledge sharing among healthcare professionals. Through integrated communication tools such as messaging and forums, medical practitioners can exchange insights, discuss challenging cases, and stay updated on the latest advancements in liver cirrhosis research and treatment.The website deployment involves rigorous testing, quality assurance, and ongoing maintenance to ensure optimal performance, data security, and compliance with healthcare regulations. Regular updates and enhancements based on user feedback and emerging research further enhance the platform's effectiveness in combating liver cirrhosis and improving patient outcomes.

In this system there can be 5 types of users i.e Healthcare Professional,Administrator,DataAnalyst/Researcher,Patient/Caregiver,Ethics Committee:

- Healthcare professionals, including physicians and specialists, have access to advanced features for data input, analysis, and patient management.
- Administrators oversee the verification process, ensure data integrity, and manage system functionalities.
- Patients may have limited access to their prediction results and educational resources to empower them in understanding their health condition and making informed lifestyle choices.
- Ethics & committee can review and approve the ethical implications of data usage and research conducted within the system and ensure that patient privacy and confidentiality are maintained throughout the predictive modeling process.

5.2.Algorithms and Flowcharts for the respective modules developed:

a) **Naïve Bayes** : It is based on the Bayes theorem of conditional probability. The algorithm assumes that each attribute contributes to the total outcome independent of other attributes .In machine learning we are often interested in selecting the best hypothesis (h) given data (d).In a classification problem, our hypothesis (h) may be the class to assign for a new data instance (d).One of the easiest ways of selecting the most probable hypothesis given the data that we have that we can use as our prior knowledge about the problem. Bayes' Theorem provides a way that we can calculate the probability of a hypothesis given our prior knowledge.

Bayes' Theorem is stated as: P(h|d) = (P(d|h) * P(h)) / P(d) Where, P(h|d) is the probability of hypothesis h given the data d. This is called the posterior probability. P(d|h) is the probability of data d given that the hypothesis h was true. P(h) is the probability of hypothesis h being true (regardless of the data). This is called the prior probability of h. P(d) is the probability of the data (regardless of the hypothesis)

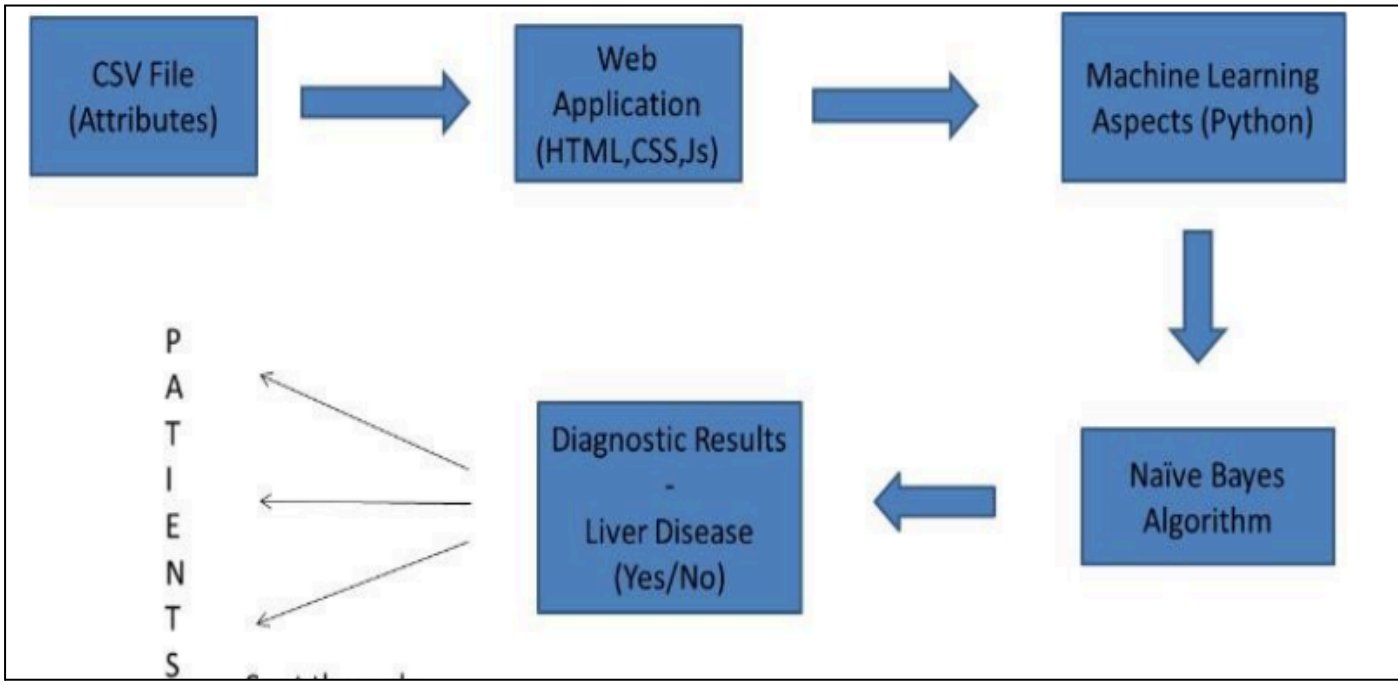


Figure 5.1: Flowchart for Liver Cirrhosis System using Naive Bayesian Algo

b) Support Vector Machine(SVM) : Several different medical applications make extensive use of classification techniques. The goal of classification is to create a model that can accurately predict the class labels of unidentified data. The training set, which comprises data points selected from the input data space together with their class labels, serves as the foundation for the model. The data is divided into two groups by a Support Vector Machine (SVM): those used for classification and those for creating an N-dimensional hyperplane. These models have close resemblance to multilayer perceptron neural networks in traditional neuroscience.In contrast to standard neural network training, which involves solving a non-convex, unconstrained minimization problem, there is an alternate training method for polynomial, radial

basis function, and multi-layer perceptron classifiers in which the weights of the network are found by solving a quadratic programming problem with linear constraints. The most popular kernel functions are sigmoid, linear, polynomial, and radial basis function (RBF), while there are many more options.

The linear kernel function used in this work is displayed in equation:

$$K(x_i,x_j)=x_iTx_j$$

The kernel parameters need to be set, depending on the type of kernel we select. Cross-validation can be used to determine the optimal kernel type, depending on the application.

A transformed attribute that is used to define the hyper plane is referred to as a feature in the SVM literature, whereas a predictor variable is considered an attribute. In this case, feature selection can be understood as selecting the best representation. A vector is a collection of features that characterizes a single case. Finding the ideal hyperplane to divide vector clusters so that instances with a single target category are kept apart is the aim of this modelling.Cases with the opposite category are on one side of the plane, and variables are on the other side of the plane.

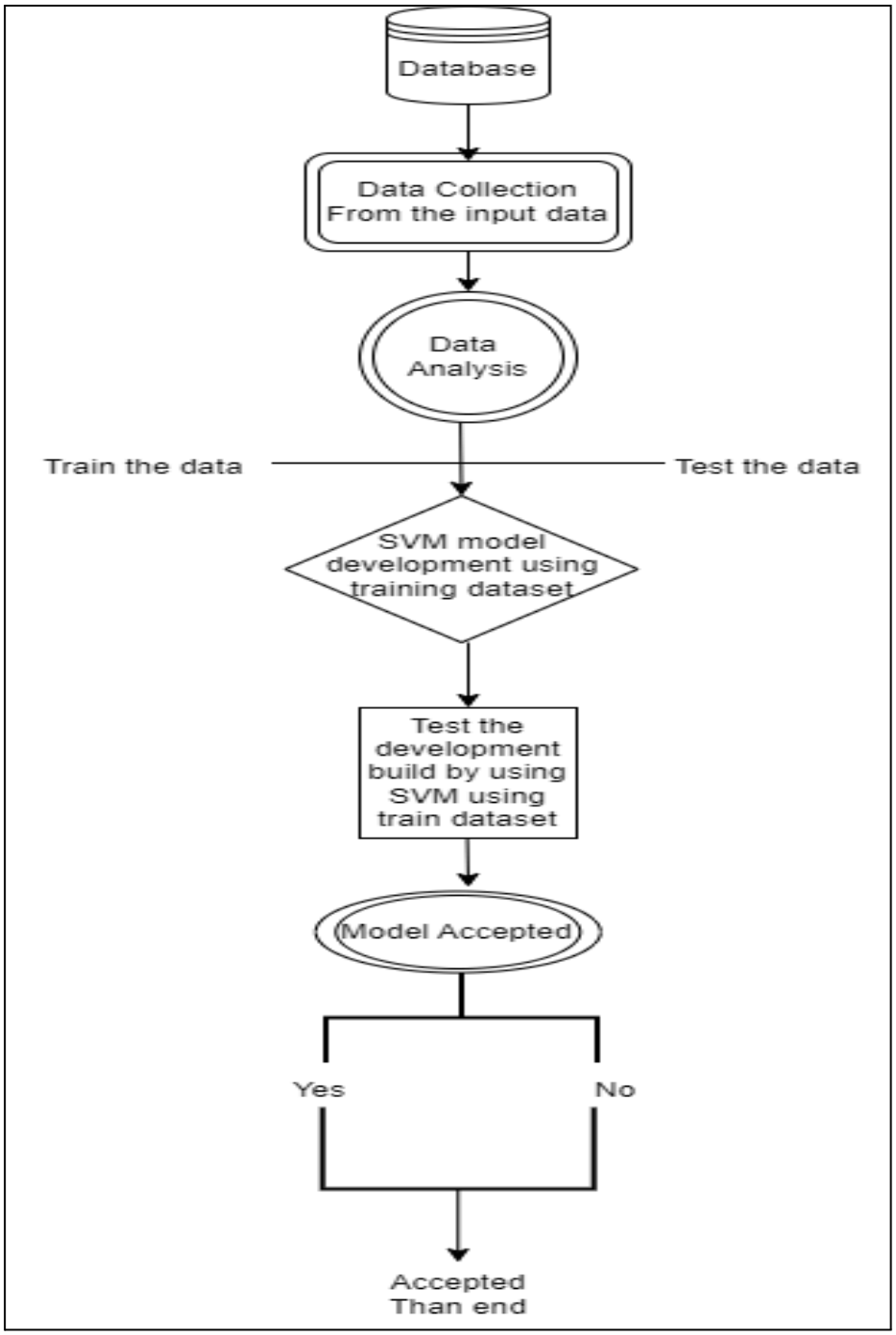


Figure 5.2: Proposed System of Liver Cirrhosis Prediction using SVM algorithm

We’ve covered some of the benefits executed by the respective algorithms. Here are a few disadvantages.

- **Sensitivity to Noisy Data**: Medical datasets, such as those pertaining to liver cirrhosis, may contain a lot of noisy data, which both the SVM and Naive Bayes algorithms are susceptible to. The accuracy of the predictive models may be negatively impacted by noisy or incorrectly labelled data points, which could result in inaccurate forecasts and impaired patient care.
- **Computational Complexity:** SVMs can require a lot of computing power, especially when working with huge datasets that are frequently used in medical research. The liver cirrhosis prediction system may face difficulties with resource requirements and model scalability due to the computational difficulty of SVM training, particularly if a significant amount of patient data needs to be processed in real-time.
- **Strong Feature Independence Assumption**: Not all features that are important for predicting liver cirrhosis will satisfy the Naive Bayes feature independence assumption. Due to this restriction, the model may not perform as well as it should since the algorithm can miss correlations and interactions between features that are critical for a precise assessment of the risk of liver cirrhosis.
- **Limited Interpretability**: SVMs, particularly in high-dimensional feature spaces, can yield complex decision boundaries that are difficult to understand and comprehend. This lack of interpretability may make it more difficult for medical practitioners to comprehend the liver cirrhosis prediction system's underlying assumptions, which could lower clinical practice's acceptance and confidence in the predictive models.

5.3.Datasets source and utilization:

The data contains the information collected from the Mayo Clinic trial in primary biliary cirrhosis (PBC) of the liver conducted between 1974 and 1984.A total of 424 PBC patients, referred to Mayo Clinic during that ten-year interval, met eligibility criteria for the randomized placebo-controlled trial of the drug D-penicillamine. The first 312 cases in the dataset participated in the randomized trial and contain largely complete data. The additional 112 cases did not participate in the clinical trial but consented to have basic measurements recorded and to be followed for survival. Six of those cases were lost to follow-up shortly after diagnosis, so the data here are on an additional 106 cases as well as the 312 randomized participants.

The dataset consists of following columns :

1. **ID:** unique identifier
2. **N_Days:** number of days between registration and the earlier of death, transplantation, or study analysis time in July 1986
3. **Status:** status of the patient C (censored), CL (censored due to liver tx), or D (death)
4. **Drug:** type of drug D-penicillamine or placebo
5. **Age:** age in [days]
6. **Sex:** M (male) or F (female)
7. **Ascites:** presence of ascites N (No) or Y (Yes)
8. **Hepatomegaly:** presence of hepatomegaly N (No) or Y (Yes)
9. **Spiders:** presence of spiders N (No) or Y (Yes)

10. **Edema:** presence of edema N (no edema and no diuretic therapy for edema), S (edema present without diuretics, or edema resolved by diuretics), or Y (edema despite diuretic therapy)
11. **Bilirubin:** serum bilirubin in [mg/dl]
12. **Cholesterol:** serum cholesterol in [mg/dl]
13. **Albumin:** albumin in [gm/dl]
14. **Copper:** urine copper in [ug/day]
15. **Alk_Phos:** alkaline phosphatase in [U/liter]
16. **SGOT:** SGOT in [U/ml]
17. **Triglycerides:** triglicerides in [mg/dl]
18. **Platelets:** platelets per cubic [ml/1000]
19. **Prothrombin:** prothrombin time in seconds [s]
20. **Stage:** histologic stage of disease (1, 2, 3, or 4)

Chapter 6: Testing of the Proposed System

6.1 . Introduction to testing

For the liver cirrhosis prediction system, we conducted rigorous testing across multiple machine learning algorithms to ascertain their efficacy. Our evaluation revealed that XGBoost exhibited the highest accuracy followed by Random Forest and SVM. This comprehensive testing process enabled us to assess the performance of each algorithm within the framework of liver cirrhosis prediction, providing valuable insights for the development and refinement of the predictive model.

6.2. Types of tests Considered

Various types of tests were considered to evaluate the liver cirrhosis prediction system comprehensively. These tests encompassed performance assessments across multiple algorithms, including

- XGBoost
- Random Forest
- SVM.

The evaluation criteria focused on accuracy metrics, measuring each algorithm's predictive capabilities across different test case scenarios. By conducting these tests, we aimed to assess the robustness, reliability, and suitability of each algorithm within the framework of liver cirrhosis prediction, thereby informing the development and refinement of the predictive model.

6.3 Various test case scenarios considered

1. Across diverse test case scenarios, **XGBoost** consistently outperformed other algorithms, boasting an impressive accuracy rate of 90%. This high level of accuracy underscores the robustness and reliability of XGBoost in predicting liver cirrhosis across different conditions and patient profiles. The algorithm's ability to handle complex data patterns and optimize predictive outcomes positions it as a formidable tool in medical diagnosis and prognosis.

2. **Random Forest**, with a respectable accuracy rate of 73%, also demonstrated notable performance in the liver cirrhosis prediction system. While slightly lower than XGBoost, its effectiveness suggests that ensemble methods such as Random Forest can provide valuable insights into disease prediction and contribute to enhancing healthcare decision-making processes. With its ability to mitigate overfitting and handle large datasets, Random Forest remains a compelling choice for predictive modeling in medical applications.
3. **SVM**, achieving an accuracy rate of 60%, presents a viable option for liver cirrhosis prediction albeit with slightly lower performance compared to XGBoost and Random Forest. Its margin-based approach to classification enables SVM to effectively delineate between different classes within the dataset. While not as high-performing in this specific context, SVM's unique characteristics make it a valuable addition to the repertoire of algorithms for medical prediction systems, offering complementary insights and perspectives in the domain of liver cirrhosis prognosis.

6.4. Inference drawn from the test cases

The test cases reveal compelling insights into the performance of various algorithms for liver cirrhosis prediction. Notably, XGBoost emerges as the top-performing algorithm, boasting a remarkable accuracy of 90%. Its consistent superiority across diverse scenarios underscores its robustness and potential for accurate diagnosis. While Random Forest and SVM exhibit slightly lower accuracies at 73% and 60% respectively, their performance reaffirms the efficacy of ensemble methods and margin-based classification approaches in medical prediction tasks. These findings collectively highlight the importance of algorithm selection in developing reliable prediction systems, with XGBoost standing out as a particularly promising choice for liver cirrhosis prognosis.

Chapter 7: Results and Discussion

7.1. Screenshots of User Interface (UI) for the respective module

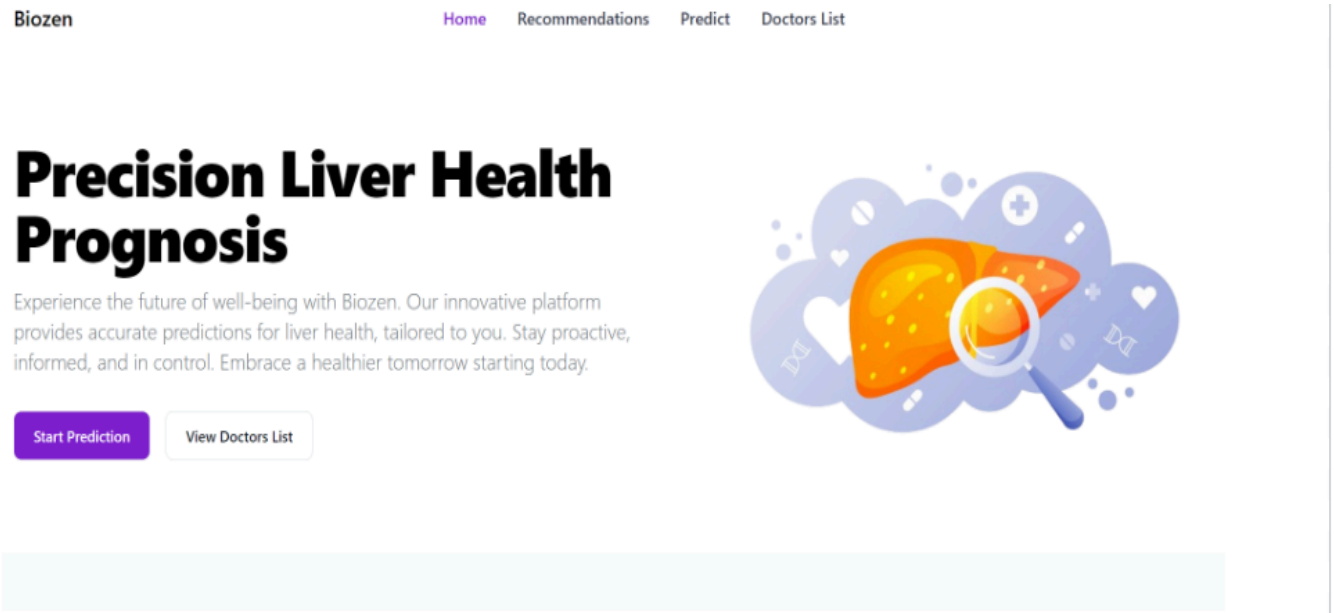


Fig 7.1 Home Page

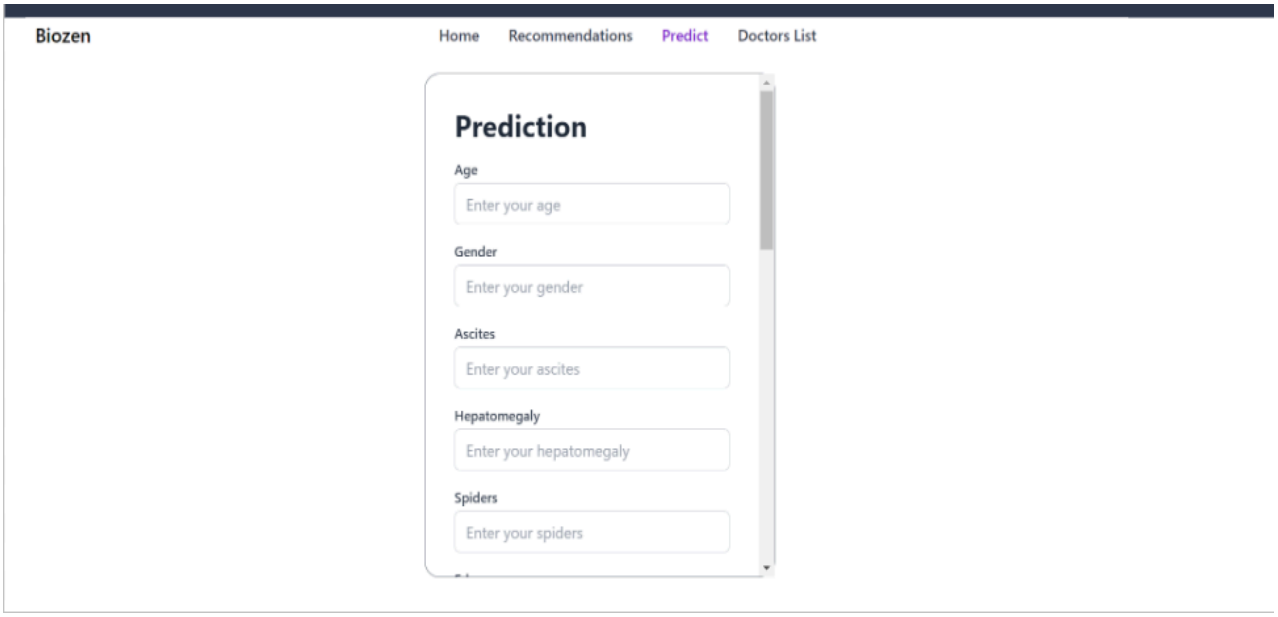


Fig 7.2 Prediction Page

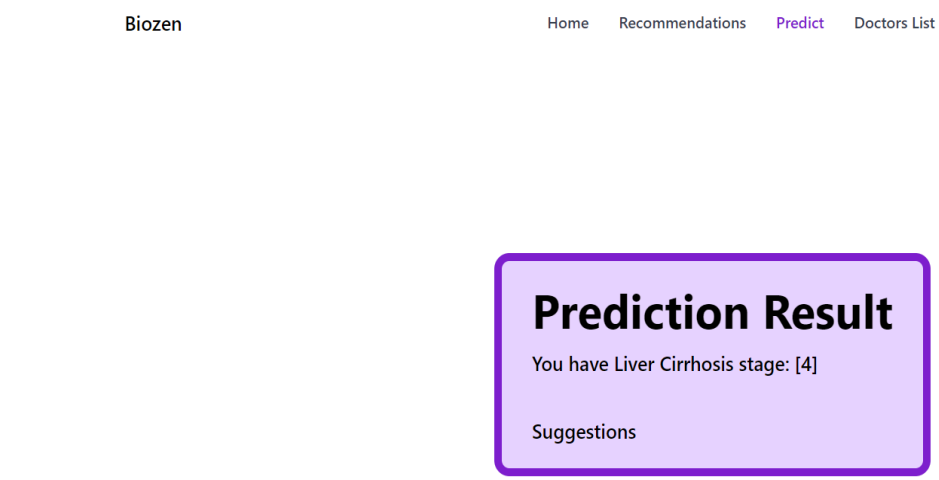


Fig 7.2.1 Prediction_Result Page

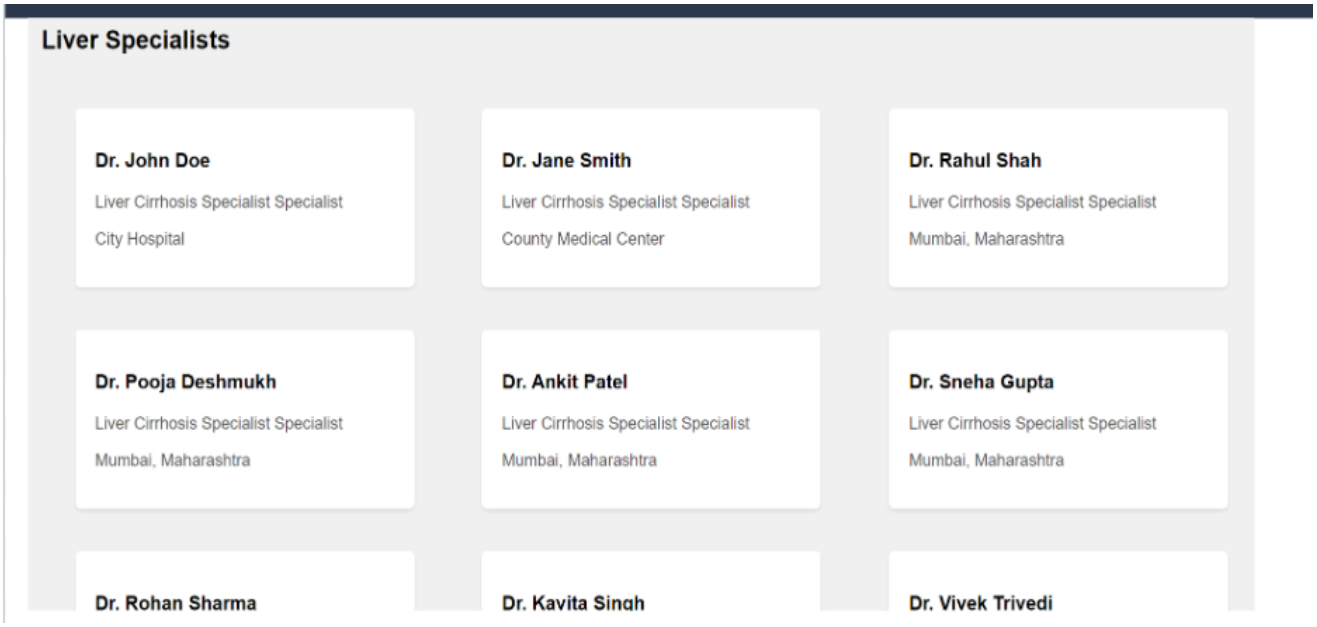


Fig 7.3 Liver Specialists Page

Fig 7.4 Know more Page

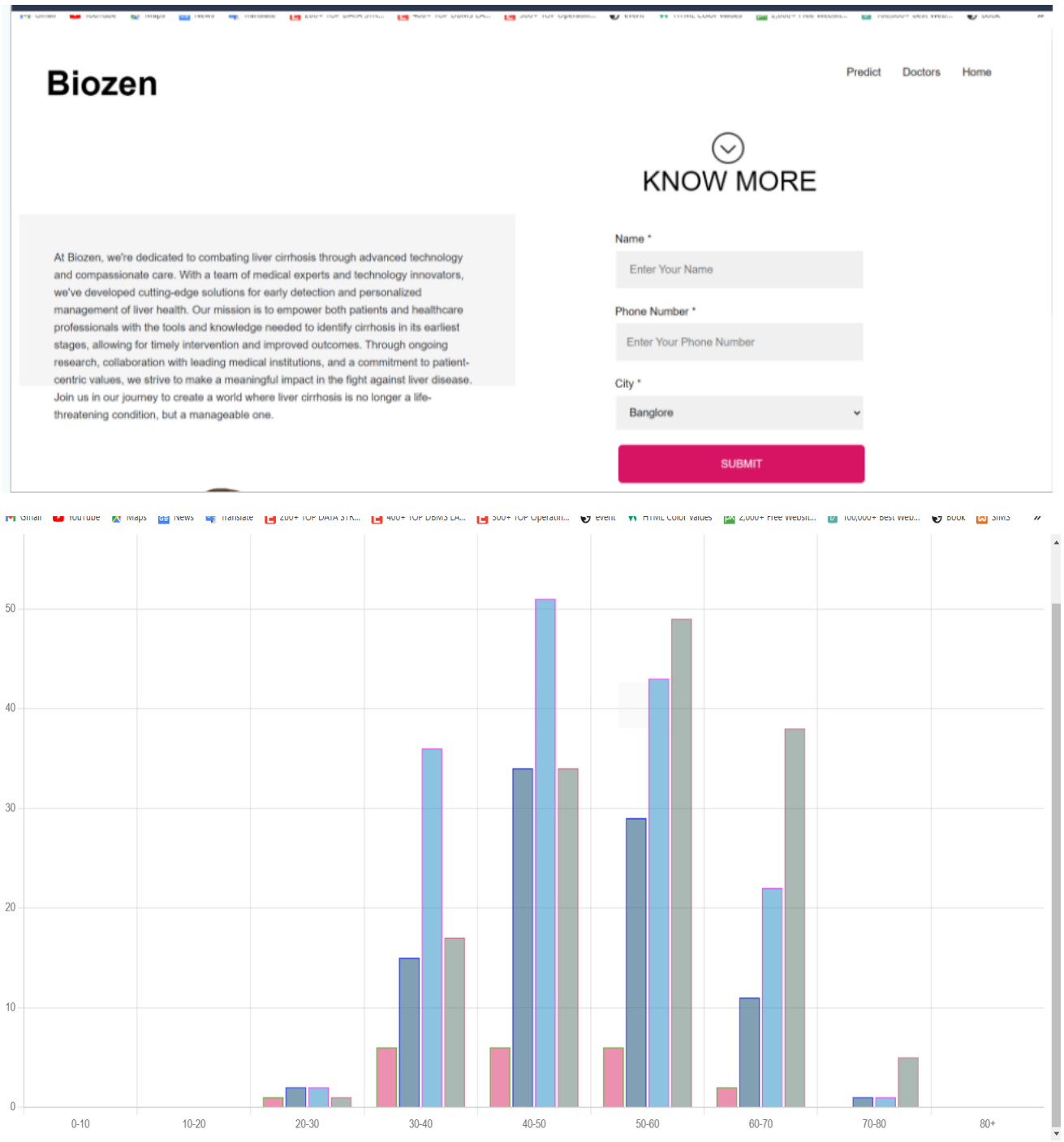


Fig 7.5 Result Analysis

7.2. Performance Evaluation measures

1. Accuracy: Accuracy refers to the proportion of correctly predicted instances (both positive and negative) out of the total instances evaluated.

Calculation: Accuracy = (TP + TN) / (TP + TN + FP + FN)

Explanation: A high accuracy score indicates that the model correctly predicts liver cirrhosis cases as positive and non-cirrhosis cases as negative, thereby minimizing misclassifications.

2.Recall (Sensitivity): Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly identify all positive instances in the dataset. It is calculated using the formula: Recall = True Positives / (True Positives + False Negatives).

In simpler terms, recall indicates the proportion of actual positive instances (cases of liver cirrhosis) that the model correctly identifies. A high recall value suggests that the model is effective at capturing most of the positive cases, minimizing the number of cases missed (false negatives). Recall is particularly important in scenarios where the cost of missing positive cases is high, such as in medical diagnosis.

3.Precision: Precision is a measure of the accuracy of positive predictions made by the model.

calculation: Precision = True Positives / (True Positives + False Positives).

Precision quantifies the proportion of true positive predictions (correctly identified instances of liver cirrhosis) among all positive predictions made by the model. A high precision value indicates that the model makes accurate positive predictions, minimizing the number of false positive predictions. Precision is especially valuable when the consequences of false positives are significant, as it ensures that the positive predictions made by the model are reliable and trustworthy.

7.3. Input Parameters / Features considered

1. **Ascites**: An accumulation of fluid in the abdomen, frequently accompanied by cirrhosis or other advanced liver disease. Low blood protein levels and elevated hepatic blood vessel pressure (portal hypertension) are the causes of it.

2. **Hepatomegaly**: Liver enlargement, frequently observed in cirrhosis and other liver disorders. It can be brought on by inflammation, fatty liver alterations, or liver tissue scarring (fibrosis).

3. **Spiders**: People with liver cirrhosis frequently have spider angiomas or spider nevi, which are tiny, dilated blood veins close to the skin's surface. They are brought on by modifications in hormone levels and blood flow brought on by liver disease.

4. **Edema**: Fluid retention-related swelling, usually in the abdomen or legs. Edema may develop in liver cirrhosis as a result of the liver's reduced ability to produce protein, which lowers blood albumin levels and raises blood vessel pressure.

5. **Bilirubin**: A yellowish pigment generated during the lysis of red blood cells. Since the liver is in charge of processing and excreting bilirubin, elevated blood bilirubin levels (hyperbilirubinemia) may be a sign of liver malfunction.

6. **Cholesterol**: A blood-borne fat type that is linked to a higher risk of cardiovascular disease at high levels. Abnormal lipid profiles can result from liver cirrhosis's impact on cholesterol metabolism.

7. **Albumin**: A liver-produced protein that carries a variety of materials, including hormones and prescription drugs, and aids in preserving blood's fluid balance.

Because liver function is compromised in liver cirrhosis, low albumin levels, or hypoalbuminemia, are frequently observed.

8. **Copper**: A vital trace mineral that is used in several different metabolic processes. A malfunction in copper metabolism in liver cirrhosis can result in an abnormal build-up of copper in the liver and other organs (Wilson's disease).

9. **Alk_Phosph**: The enzyme alkaline phosphatase is present in the liver, bones, and bile ducts, among other tissues. Increased blood levels of alkaline phosphatase could be a sign of bone or liver illness, particularly cirrhosis of the liver**.**

10. **Serum Glutamic Oxaloacetic Transaminase, or SGOT**: This enzyme, which is present in the liver and other tissues, is also referred to as AST (aspartate aminotransferase). Increased blood levels of SGOT may be a sign of inflammation or injury to the liver, both of which can happen in liver cirrhosis.

11. **Trygliceride**s: The blood contains a form of fat called triglycerides. Increased risk of cardiovascular disease is linked to elevated triglyceride levels. Triglyceride levels may be impacted by changes in lipid metabolism brought on by liver cirrhosis.

12. **Platelets**: Blood components that aid in coagulation. Due to decreased production by the diseased liver or greater sequestration in the spleen, platelet counts may drop in liver cirrhosis, increasing the risk of bleeding.

13. **Prothrombin**: The duration of blood clotting is measured by prothrombin time (PT). The liver's capacity to manufacture clotting factors may be compromised by liver cirrhosis, which may result in longer parenchyma therapy and a higher risk of bleeding.

7.4. Graphical and statistical output

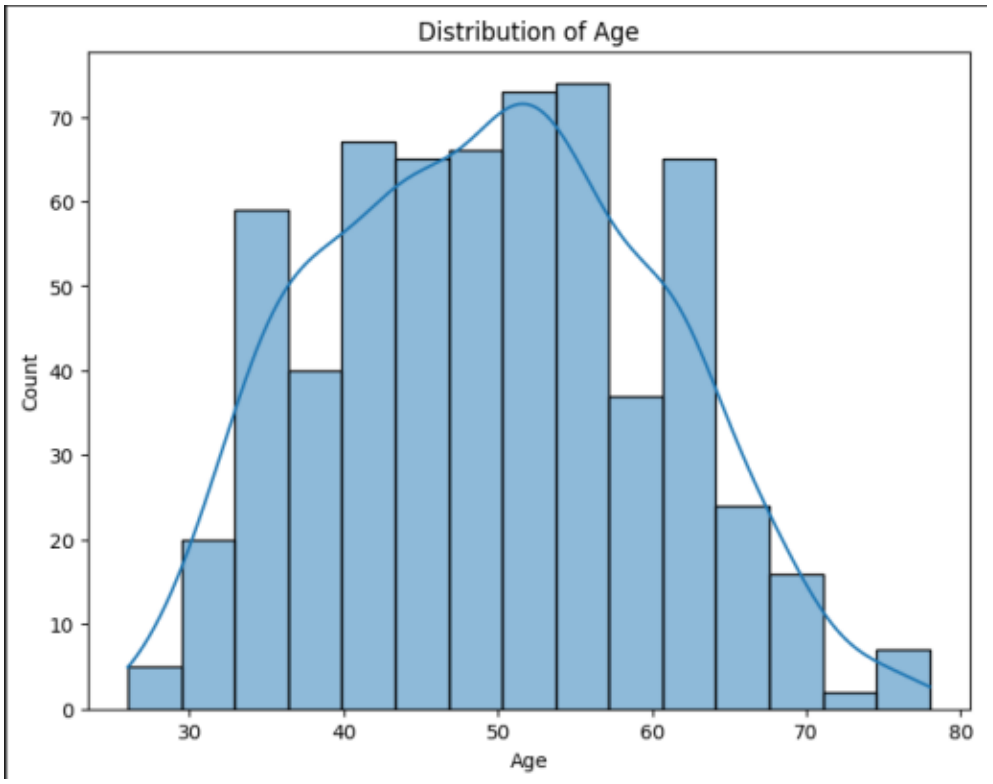


Fig 7.4.1 Distribution of age

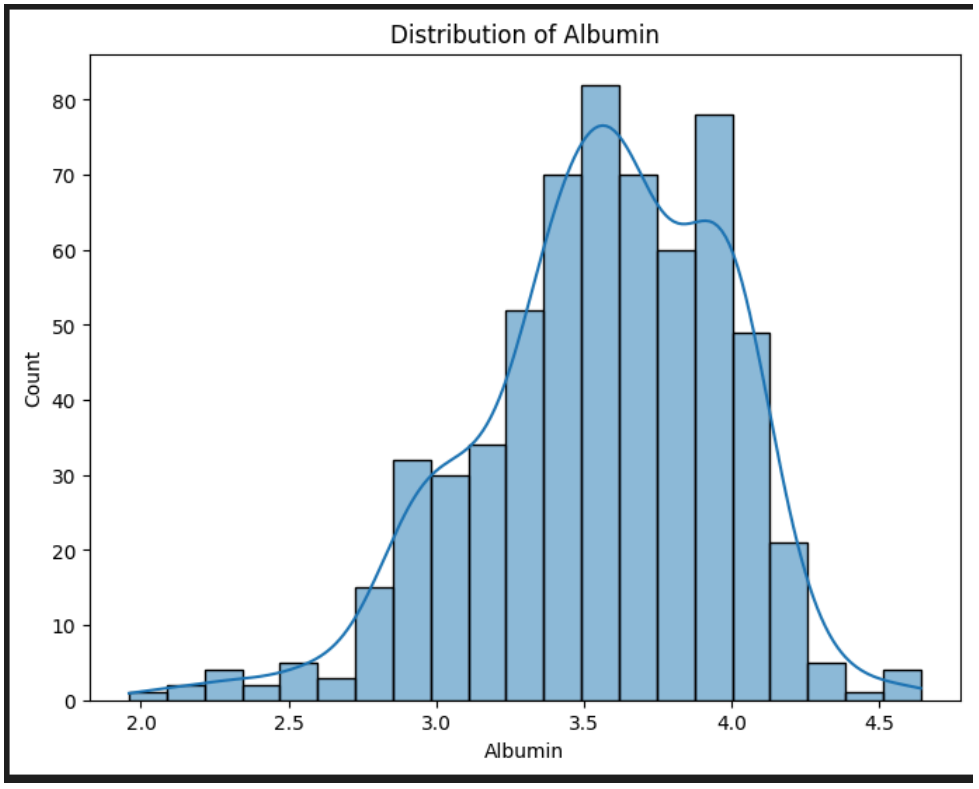


Fig 7.4.2 Distribution of Albumin

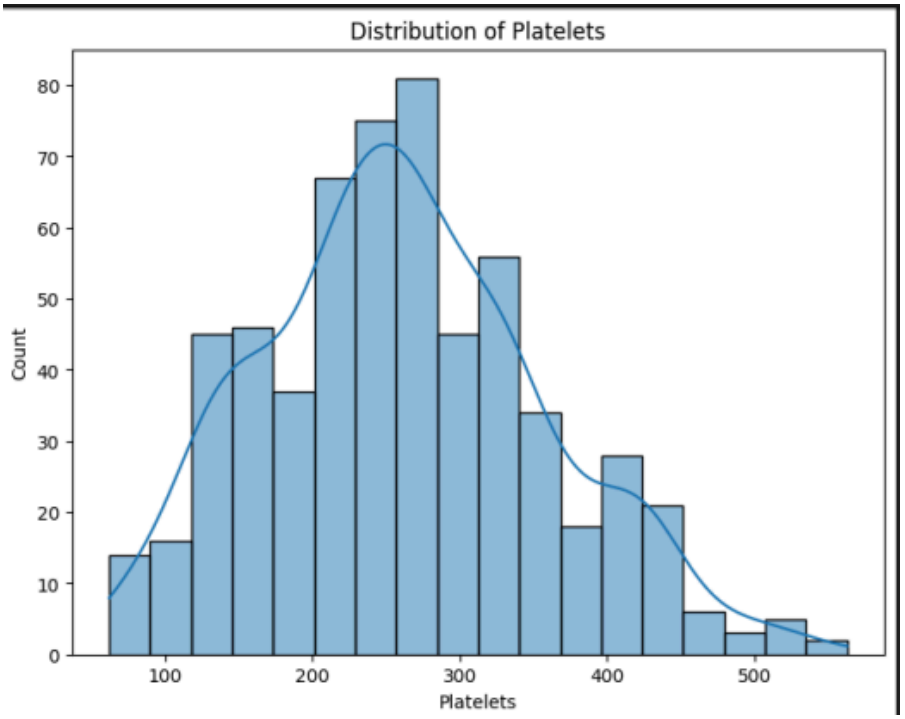


Fig 7.4.3 Distribution of Platelets

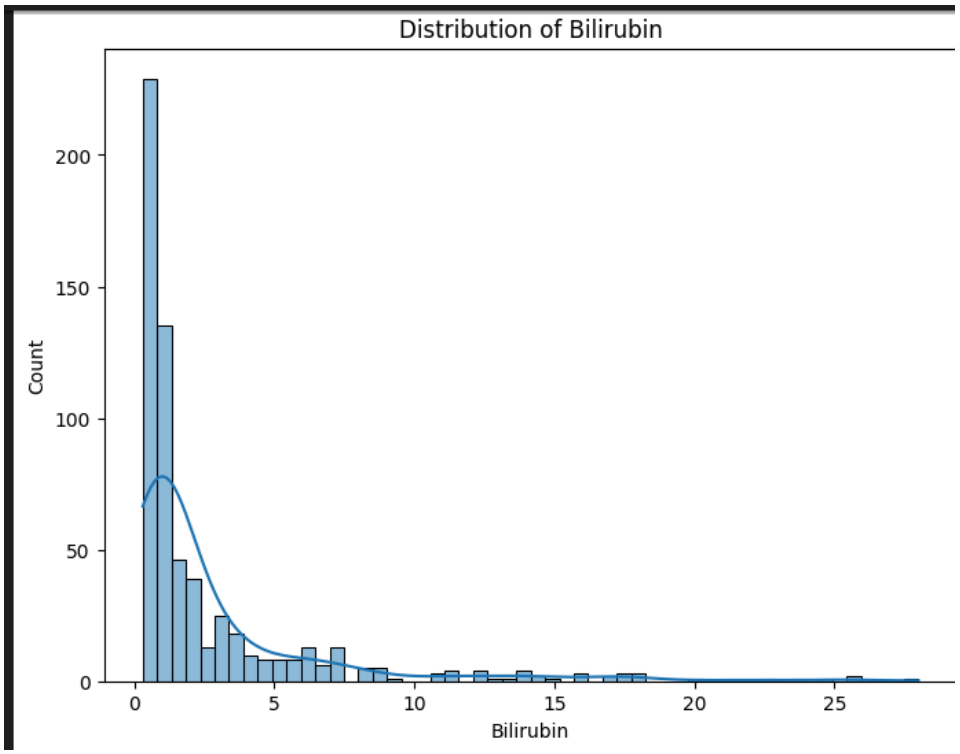


Fig 7.4.4 Distribution of Bilirubin

7.5. Comparison of results with existing systems

- When comparing the results of the liver cirrhosis prediction system with existing systems, several challenges and limitations become apparent. Firstly, problems with data quality pose a significant obstacle. The completeness, representativeness, and overall quality of the training data directly impact the predictive ability of any data model. Issues such as missing values, errors, or biases within the data can compromise the reliability and generalizability of the model's predictions.
- Secondly, feature selection bias can significantly affect the performance of the prediction model. The predictive power of the model heavily relies on the characteristics chosen as input variables. However, flawed selection methods may lead to the exclusion of crucial factors or the inclusion of insignificant ones, potentially resulting in skewed forecasts or suboptimal model performance.
- Thirdly, the limited availability of datasets presents a considerable challenge. The reliability of liver cirrhosis prediction classifiers is hindered by the scarcity of available data. While thousands of data points per class would be ideal for improving classifier accuracy, the reality often falls short due to dataset shortages. Consequently, researchers are continually exploring alternative approaches to develop reliable classifiers for the prediction of liver cirrhosis. These challenges underscore the need for ongoing efforts to address data quality issues, minimize feature selection bias, and expand available datasets to enhance the accuracy and effectiveness of liver cirrhosis prediction systems.

7.6. Inference drawn

The comparison of results with existing systems highlights several key inferences regarding liver cirrhosis prediction. Firstly, it underscores the critical importance of addressing data quality issues to ensure the reliability and generalizability of predictive models. Secondly, it emphasizes the need for careful consideration and refinement of feature selection methods to mitigate bias and improve model performance. Lastly, the scarcity of available datasets poses a significant challenge, necessitating ongoing efforts to expand and diversify data sources for more accurate predictions. These inferences underscore the complexity of liver cirrhosis prediction and underscore the importance of continued research and development efforts to overcome these challenges and improve the effectiveness of prediction systems in clinical practice

Chapter 8: Conclusion

8.1 Limitations

1. **Problems with Data Quality:** The completeness, representativeness, and quality of the training data have a significant impact on any data model's ability to predict outcomes. The reliability and generalizability of the model's predictions may be jeopardized by limitations in the quality of the data, such as missing values, errors, or bias.

2. **Feature Selection Bias**: The data model's prediction performance is largely dependent on the characteristics that are chosen as input. However, the selection method might have flaws, including leaving out important factors or including ones that aren't significant, which could result in skewed forecasts or less-than-ideal model performance.

3. **Limited available datasets:** The reliability of liver cirrhosis prediction classifiers is hindered by the scarcity of available datasets. Thousands of photos per class would be ideal to improve the classifiers' accuracy . Nevertheless, inadequate training data is frequently the consequence of dataset shortage. As a result, scientists are always looking into different approaches to develop trustworthy classifiers for the prediction of liver cirrhosis.

8.2 Conclusion

In conclusion, the Liver Cirrhosis Detection System represents a significant stride forward in the realm of healthcare and medical diagnostics. By leveraging advanced machine learning techniques and comprehensive patient data analysis, this system offers a promising solution to the persistent challenge of timely liver cirrhosis detection.

The system's ability to predict cirrhosis risk and facilitate early intervention holds the potential to transform patient outcomes, reduce healthcare costs, and alleviate the burden on healthcare systems.

8.3 Future Scope

Looking ahead, liver cirrhosis prediction systems show promise for significant advancement. Technologies like AI and machine learning can enhance accuracy by analyzing diverse datasets. Incorporating novel biomarkers and advanced imaging may improve early detection and disease assessment. Integration with remote monitoring and telemedicine enables proactive patient management. Future systems could personalize risk assessment and treatment strategies based on individual factors. These advancements aim to improve outcomes and optimize care for patients with chronic liver disease.

References

1]Jagdeep Singh, Sachin Bagga, Ranjodh Kaur,"Software-based Prediction of Liver Disease with Feature Selection and Classification Techniques", Procedia Computer Science, Volume 167,2020, Pages 1970-1980, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.03.226. (https://www.sciencedirect.com/science/article/pii/S187705092030692X)

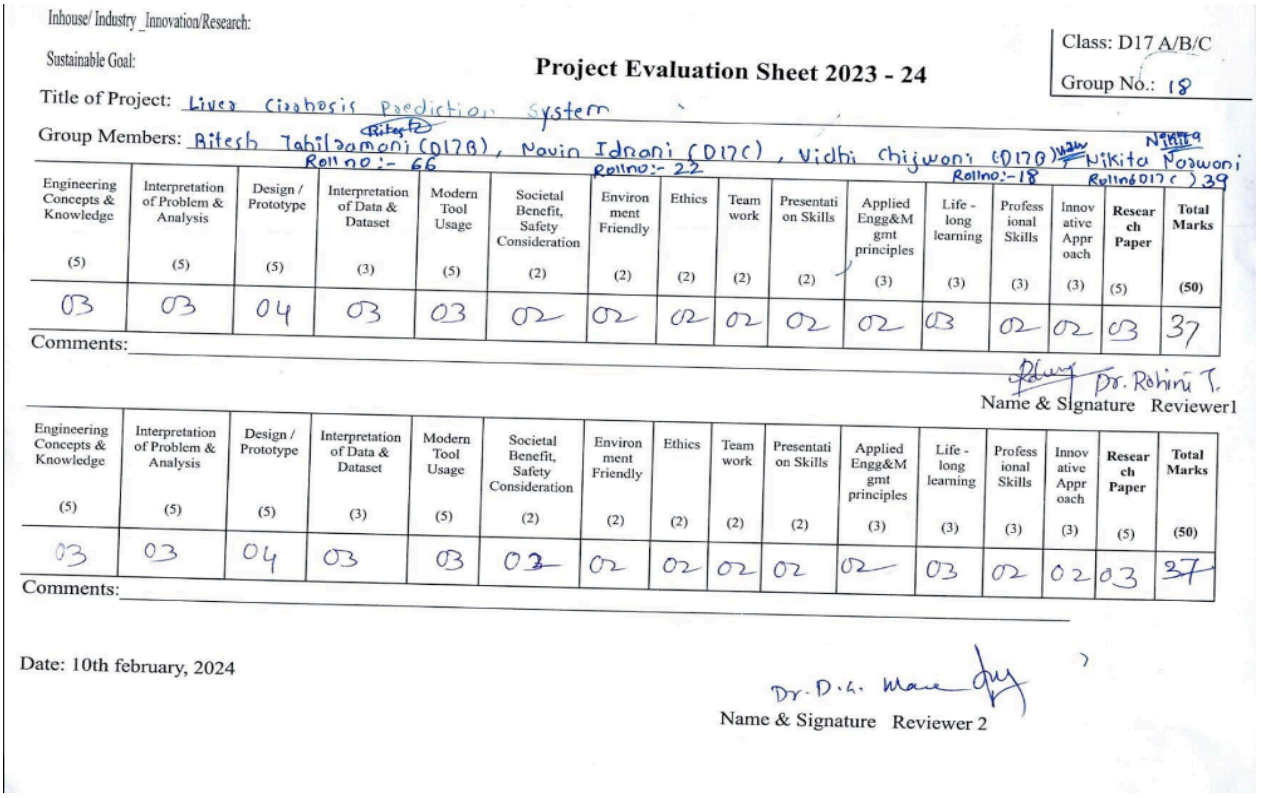
[2] Sreenivasa Rao Veeranki and Manish Varshney ,” Intelligent Techniques and Comparative Performance Analysis of Liver Disease Prediction”, Procedia Computer Science, ISSN: 0974-5823 Vol. 7 No. 1 January 2022 . (https://kalaharijournals.com/resources/IJME_Vol7.1_756.pdf)

[3] E Snayan Yadav , Bachepalli Sanhitha , and M Krishna Prasanna.,”Liver Disease Prediction using Machine Learning” ,Department of Information Technology,B V Raju Institute of Technology,Vol-9 Issue-2 2023 IJARIIE-ISSN(O)-2395-4396.

[4]Ruhul Amin, Rubia Yasmin, Sabba Ruhi, Md Habibur Rahman, Md Shamim Reza,"Prediction of chronic liver disease patients using integrated projection based statistical feature extraction with machine learning algorithms”,Informatics in Medicine Unlocked,Volume 36,2023,101155,ISSN-2352-9148,https://doi.org/10.1016/j.imu.2022.101155. https://www.sciencedirect.com/science/article/pii/S2352914822002921

[5]Velu, S.R., Ravi, V. & Tabianan, K. “Data mining in predicting liver patients using a classification model”. Health Technol. 12, 1211–1235 (2022). https://doi.org/10.1007/s12553-022-00713-3. https://link.springer.com/article/10.1007/s12553-022-00713-3

Project Review Sheet:



Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C

Group No.: 18

Title of Project: Liver Cirrhosis Prediction System

Group Members: Ritesh Tahilramani (D17B), Navin Idnani (D17C), Vidhi Chijwani (D17B), Nikita Nazwani Roll no:- 66 Roll no:- 22 Roll no:- 18 Roll no:- 39

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
03	03	04	03	03	02	02	02	02	02	02	03	02	02	03	37

Comments:

Dr. Rohini T.

Name & Signature Reviewer1

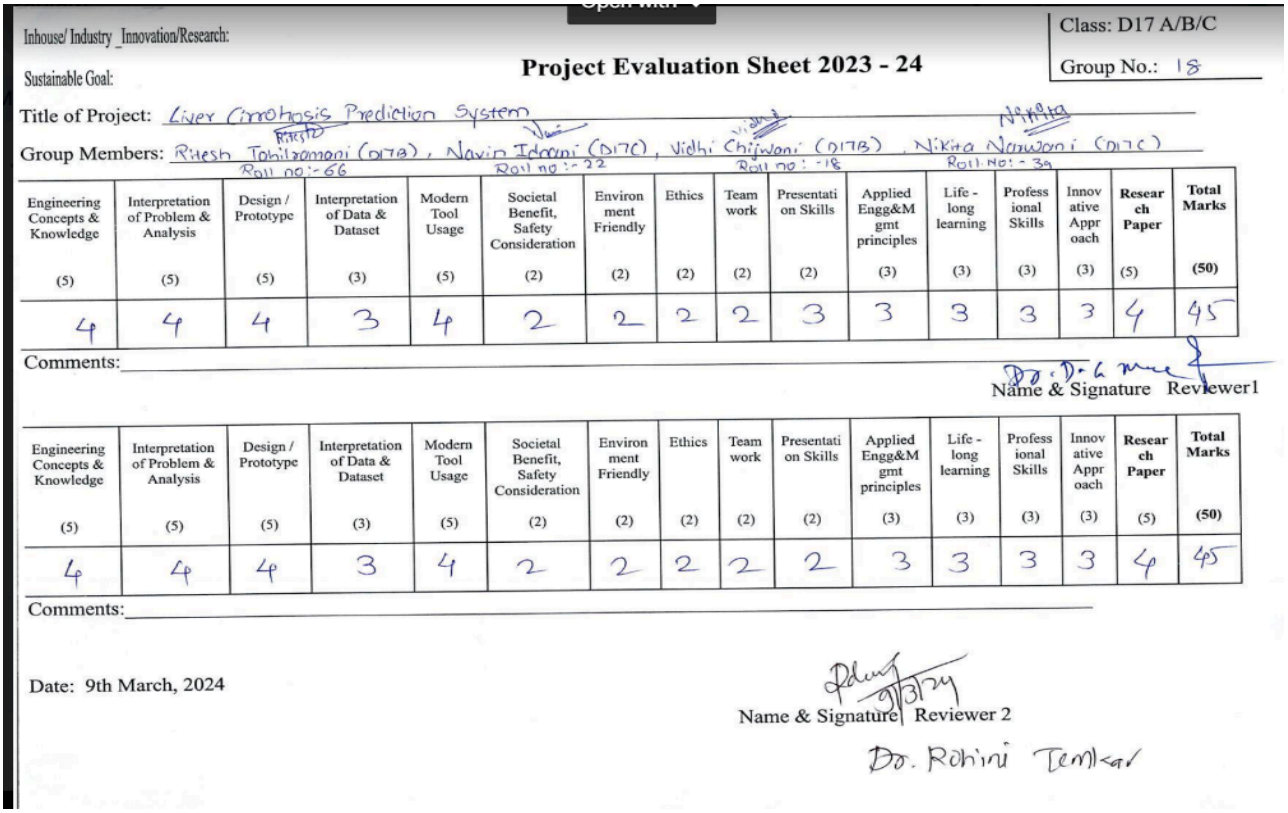
Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
03	03	04	03	03	02	02	02	02	02	02	03	02	02	03	37

Comments:

Date: 10th february, 2024

Dr. D. G. Mane

Name & Signature Reviewer 2



Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2023 - 24

Class: D17 A/B/C

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Comments:

Dr. D. G. Mane

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
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Comments:

Date: 9th March, 2024

9/3/24

Name & Signature Reviewer 2

Dr. Rohini Temkar