### 1. INTRODUCTION

### 1.1 project overview

The project titled "Revolutionizing Liver Care: Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques" aims to develop a predictive model to detect the onset or progression of liver cirrhosis in patients. By analyzing diverse patient data—including medical history, lab results, imaging scans, and lifestyle factors—the model seeks to assess the likelihood of liver cirrhosis, thereby assisting healthcare professionals in making informed decisions about patient care. <a href="mailto:github.com">github.com</a>

#### **Key Features of the Project:**

- **Multimodal Data Integration:** The model incorporates various data types such as clinical records, laboratory results, imaging data, and lifestyle information to provide a comprehensive risk assessment.
- Machine Learning Algorithms: Advanced machine learning techniques are employed to analyze the integrated data, aiming to predict the likelihood of liver cirrhosis with high accuracy.

#### • Clinical Applications:

- Patient Screening: The predictive model can be integrated into electronic health records (EHR) systems to assess the risk of liver cirrhosis during routine check-ups or when patients present symptoms associated with liver issues.
- Treatment Planning: For patients already diagnosed with liver disease, the model assists in treatment planning by predicting the progression of liver cirrhosis, allowing for tailored treatment strategies.
- Resource Allocation: Healthcare facilities can utilize the model to optimize resource allocation by identifying high-risk patients who require closer monitoring and timely intervention.github.com
- **Open-Source Availability:** The project is open-source and licensed under the MIT License, encouraging collaboration and further development by the research community.

#### ☐ Project Details (by Vrushika K. Panchal)

Based on a LinkedIn announcement:

- End-to-end workflow: Covers data collection, preprocessing (handling missing values), exploratory analysis, encoding, and train-test splits mdpi.com+15linkedin.com+15skillwallet.smartinternz.com+15.
- Algorithms evaluated: Random Forest, SVM, Logistic Regression, XGBoost, and K-Nearest Neighbors (KNN). KNN achieved the best overall performance linkedin.com+1researchgate.net+1.
- **Key metrics presented**: Accuracy, F1-score, recall, precision, with individualized confusion matrices <u>linkedin.com</u>.

- **Dataset used**: Publicly available dataset—likely a standard liver disease dataset (e.g., UCI repository)—accessible via project link <u>aeis.bilijipub.com+5linkedin.com+5arxiv.org+5</u>.
- **Deployment**: The model is wrapped in a Flask web app, enabling users to input patient data and receive real-time risk predictions <a href="mailto:f
- **Open-source**: Hosted on GitHub under an MIT license, inviting community collaboration journals.plos.org+11mdpi.com+11arxiv.org+11.

#### Related ML & Al Advances in Liver Cirrhosis Research

- Hybrid classifier approach: A recent arXiv preprint (Apr 2025) describes combining ultrasound image analysis (DenseNet-201) with blood-test features using a voting classifier model, achieving ~92.5% accuracy in detecting liver fibrosis/cirrhosis fmaihub.com+2arxiv.org+2pubmed.ncbi.nlm.nih.gov+2.
- Deep learning on MRI: Another Apr 2025 deep learning model analyzes multi-sequence MRI
  to classify cirrhosis into three stages, achieving ~73% on T1-weighted scans and ~64% on T2weighted scans <u>arxiv.org</u>.

These signal a trend toward **multimodal models**—integrating imaging, labs, and clinical data for more nuanced predictions, which complements the Vrushika project focused on tabular/classifier approaches.

### **✓** Project Strengths & Opportunities

Strengths	Opportunities for Growth
Clear end-to-end pipeline with Flask deployment and confusion-matrix visualizations <u>linkedin.com</u>	Could extend to multimodal data (imaging, EHR text, ultrasound) to improve performance
KNN-based model is intuitive and interpretable	Testing on larger, more diverse datasets (e.g., from hospitals or EHR systems) for robustness
Open-source release encourages community feedback	Incorporating deep learning models (CNNs on imaging or transformer-based on EHR data)

#### Where This Fits in the Research Landscape

- Al-driven EHR analysis: A study analyzed clinical notes using CNNs, achieving ~97% precision on cirrhosis cases—highlighting the potential of text-based AI models <a href="mailto:f
- **Imaging + clinical fusion models**: The Apr 2025 hybrid study merges imaging and blood data for robust fibrosis detection .

#### 1.2 Purpose

### **Primary Objectives**

#### 1. Early Detection

 Employ algorithms trained on patient data—including medical history, lab tests, imaging results, and lifestyle factors—to detect cirrhosis onset or progression before symptoms appear pmc.ncbi.nlm.nih.gov+2github.com+2epbl-livercare-flaskappteam-ymim.onrender.com+2.

### 2. Enhance Clinical Decision Making

 Provide doctors with actionable risk scores that integrate seamlessly into daily workflows (e.g., EHR systems), supporting decisions like ordering additional tests or referring to specialists mdpi.com.

### 3. Optimize Treatment and Monitoring

 Track disease trajectory in patients already diagnosed with liver conditions, enabling personalized intervention and medication adjustments to slow progression <a href="ncbi.nlm.nih.gov+4github.com+4probiologists.com+4">ncbi.nlm.nih.gov+4github.com+4probiologists.com+4</a>.

### 4. Improve Healthcare Resource Allocation

 Help healthcare providers focus resources (e.g., specialist care, imaging, monitoring) on patients flagged at high risk—saving time, costs, and reducing unnecessary testing.

### Context & Value

- Non-invasive alternative: Offers a less intrusive method compared to liver biopsies by leveraging existing clinical and laboratory data <u>en.wikipedia.org+11epbl-livercare-flaskapp-team-</u> ymim.onrender.com+11probiologists.com+11.
- Proactive care: Supports early intervention, which can significantly improve patient outlook and reduce complications.
- Data-driven alignment: Taps into the broader healthcare trend toward Albased risk models—similar to successful systems like MELD-Plus and LightGBM-based fibrosis predictors en.wikipedia.org+1mdpi.com+1.

### Summary

The core purpose is to revolutionize liver care by creating a machine learning-powered tool that:

- Detects cirrhosis earlier and more accurately
- Integrates smoothly into clinical workflows
- Guides personalized treatment and monitoring
- Enhances efficiency in healthcare delivery

## **©** Core Purpose

- 1. Early, Non-Invasive Detection of Cirrhosis
  - Leverage machine learning on routine patient data—blood tests, demographics, lifestyle, and potentially imaging—to identify cirrhosis before symptoms manifest, reducing reliance on invasive procedures like biopsies. Early detection supports timely interventions and lessens complications researchgate.net+1ijisae.org+1arxiv.org+8ncbi.nlm.nih.gov+8pmc. ncbi.nlm.nih.gov+8.

### 2. Clinical Decision Support & Integration

- Deliver interpretable risk scores to clinicians via EHR-integrated tools (e.g., the project's Flask web app), guiding decisions on further testing, specialist referrals, or lifestyle recommendations enhancing day-to-day medical workflows <a href="mailto:shmpublisher.com">shmpublisher.com</a>.
- 3. Personalized Treatment and Monitoring
  - Use ongoing predictions to track cirrhosis progression in known patients, enabling bespoke care strategies and therapy adjustments before severe complications occur.
- 4. Optimized Use of Healthcare Resources
  - Prioritize diagnostic imaging, specialist follow-ups, and monitoring for high-risk individuals, which conserves medical resources and reduces unnecessary testing—all while improving patient outcomes.

### Why It Matters Now

Recent biomedical AI research has increasingly focused on multimodal integration:

- Hybrid ultrasound + blood-test models have shown ~92.5% accuracy for fibrosis/cirrhosis detection ijisae.org+14arxiv.org+14arxiv.org+14.
- MRI-based deep learning systems are now classifying cirrhosis stages with 63–73% accuracy mdpi.com+14arxiv.org+14pmc.ncbi.nlm.nih.gov+14.
- Triple-modality fusion networks (clinical, radiomic, and imaging data) are emerging for improved prognosis <u>arxiv.org</u>.

Within this scientific landscape, the Vrushika-led project provides a critical baseline for purely tabular, classical ML approaches—offering a foundation that future efforts can build upon by integrating imaging or text data for richer, multimodal detection.

### **Q** Summary of Purpose

### The project aims to:

Goal	Impact
Detect cirrhosis earlier	Improve patient outcomes & reduce invasive testing
Provide actionable risk scores	Aid clinicians through clear, interpretable guidance
Track disease progression	Allow tailored treatment and monitoring plans
Optimize healthcare resources	Target interventions to those who need it most

### 2. IDEATION PHASE

### 2.1 Define the Problem Statements

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	2 Marks

## **Customer Problem Statement Template:**

A Customer Problem Statement Template is a structured format that helps identify and clearly articulate the real issues or pain points faced by patients, caregivers, or healthcare providers in the context of liver care. In the journey to revolutionize liver care, this tool is crucial for ensuring that innovation efforts are rooted in real needs rather than assumptions.

# Why Use a Customer Problem Statement in Liver Care?

- Focuses innovation efforts on real-world problems
- Helps align teams (clinicians, researchers, tech, business) on a common goal
- Drives empathy for patients, caregivers, and doctors
- Acts as a foundation for solution ideation and validation

☐ Template: Customer Problem Statement (Liver Care Focus)

Here's a structured template with guiding questions:

### 1. Customer Segment

Who is experiencing the problem? (e.g., Chronic liver disease patients, caregivers, hepatologists, primary care physicians)

Example: Patients with non-alcoholic fatty liver disease (NAFLD)

## 2. Problem Description

What is the core problem or pain they are experiencing?

Focus on symptoms, inefficiencies, or emotional struggles.

Example: Patients often don't get diagnosed until latestage liver disease because early symptoms are vague and routine screening is not emphasized.

## 3. Context / Environment

When and where does the problem occur? Look at workflows, settings (home, clinics), or technology gaps.

Example: In primary care settings where liver health is not proactively monitored.

## 4. Current Alternatives / Workarounds

How is the problem currently being handled? What are the limitations?

Example: Liver function tests are ordered only when liver disease is suspected; many cases go undetected in early stages.

## 5. Consequences of the Problem

What is the impact of this problem if it is not solved?

Example: Late diagnosis leads to higher treatment costs, worse outcomes, and increased

## 6. Emotional / Human Insight

What are the emotional or behavioral insights about the user?

Example: Patients feel anxious due to lack of clarity about their liver health and feel neglected in preventive care conversations.

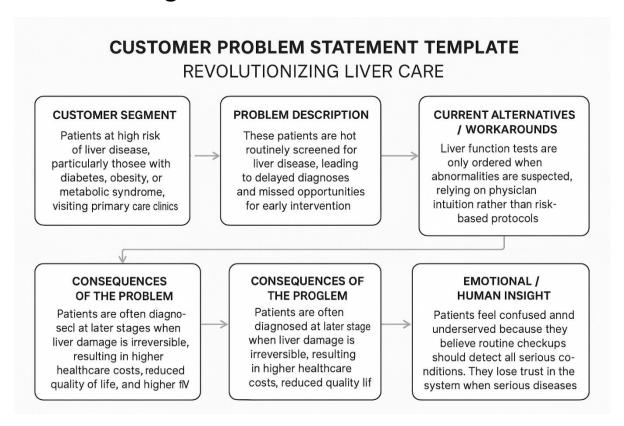
## **©** Example Statement

"Primary care patients with risk factors for liver disease (like obesity and diabetes) are not being proactively screened, leading to late diagnoses and avoidable complications. This occurs because liver care is often reactive, not integrated into routine checkups. As a result, patients feel overlooked, and doctors miss early intervention opportunities."

## Tips for Writing an Effective Statement

- Use real quotes or observations from interviews, if available.
- Avoid suggesting solutions focus only on defining the problem.
- Be concise but rich in context and empathy.

 Revisit and refine the statement as you gather more insights.



### **Example:**

## **Example 1: Early Detection in Primary Care**

- Customer Segment: Adults with obesity, diabetes, or metabolic syndrome visiting general practitioners.
- Problem Description: These high-risk patients are not routinely screened for liver disease in primary care settings.

- Context: Liver function assessment is often overlooked during regular checkups due to lack of standard screening protocols.
- Current Workarounds: Tests are only ordered based on visible symptoms or abnormal labs, which often appear too late.
- Consequences: Late diagnosis of conditions like NAFLD/NASH leads to irreversible liver damage and increased treatment burden.
- Emotional Insight: Patients assume annual checkups cover major health risks, leading to confusion and frustration when liver disease is diagnosed unexpectedly.

## Example 2: Post-Transplant Follow-up Gaps

- Customer Segment: Liver transplant recipients and their caregivers.
- Problem Description: Patients struggle to manage complex follow-up care after transplant, leading to complications.
- Context: Post-discharge care is fragmented, with poor communication between transplant centers and local providers.

- Current Workarounds: Patients rely on handwritten notes, multiple apps, or informal caregiver support.
- Consequences: Medication non-adherence, missed appointments, and preventable hospital readmissions.
- Emotional Insight: Patients feel overwhelmed, anxious, and unsupported during a critical recovery period.

## 2.2Empathize & Discover

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	4 Marks

## **Empathy Map Canvas:**

☐ What is an Empathy Map Canvas?

An Empathy Map Canvas is a structured framework that captures what a person says, thinks, does, and feels in a specific context. In revolutionizing liver care, it is used to:

- Understand the emotional and behavioral experience of patients and stakeholders.
- Align team members around real, human-centered problems.
- Identify unmet needs that can lead to transformative solutions.

## **Why Use It in Liver Care?**

Liver diseases—like NAFLD, cirrhosis, or hepatitis—often progress silently, with low awareness among patients and even primary care providers. An empathy map helps uncover:

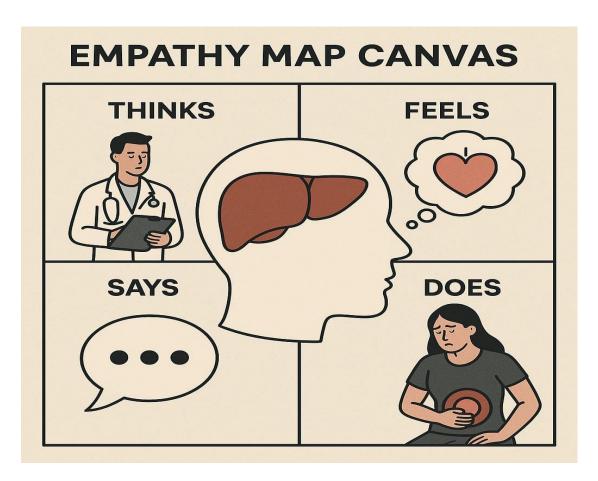
- Emotional responses to diagnosis and treatment
- Barriers in access, communication, and care continuity
- Misconceptions about liver health
- Caregiver challenges in post-transplant or chronic management

## Use Cases in Liver Care Innovation

- Designing a patient education app
- Creating a screening protocol in primary care
- Improving transplant patient aftercare
- Developing telehealth tools for remote patients

<b>Empathy Map Canvas Template (Summary Layout)</b>
SAYS   THINKS
What they say   Inner voice
DOES   FEELS
Behavior   Emotions
PAINS
Frustrations, obstacles
GAINS

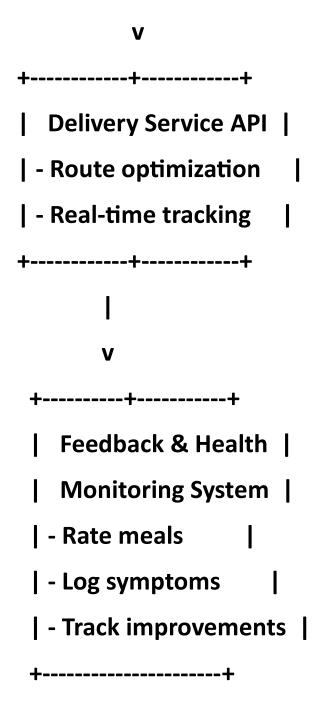
## **Example:**



**Example: Food Ordering & Delivery Application:** 

+-----+
| Patient/End User |
|(Mobile App Interface) |
+-----+
|
v

```
Personalized Meal Planner
  | (Based on liver condition,
  | doctor/dietician input)
  Doctor/Dietician Dashboard
| - Set meal plans
| - Track compliance
| - Monitor nutrition reports
    Food Vendor Management
 | - Partnered liver-friendly
    kitchens/restaurants
 I - Menu customization
```



### 2.3 Brainstorm & Idea Prioritization Template

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care
	:Predicting Liver Cirrhosis

	Using Advanced Machine		
	Learning Techniques		
Maximum Marks	4 Marks		

### **Brainstorm & Idea Prioritization Template:**

### ☐ Ideation Phase: Overview

The Ideation Phase is a creative and strategic stage in the innovation process. It focuses on generating, developing, and prioritizing ideas that can solve a defined problem or improve existing solutions.

### **G** Goal:

Generate innovative and actionable ideas to revolutionize liver care by improving prevention, diagnosis, treatment, or post-treatment support.

### ☐ Key Activities in the Ideation Phase

- 1. Define the Challenge:
  - o What are the current gaps or pain points in liver care?
  - Are we focusing on liver disease prevention, diagnosis, treatment, or patient follow-up?

#### 2. Brainstorm Ideas:

- Encourage open and diverse thinking without judgment.
- Use various brainstorming techniques like:
  - SCAMPER (Substitute, Combine, Adapt, Modify, Put to another use, Eliminate, Reverse)
  - Crazy 8s (8 ideas in 8 minutes)
  - Mind Mapping
  - Reverse Thinking

### 3. Group & Refine Ideas:

- Categorize similar ideas.
- $_{\circ}$   $\;$  Identify themes or commonalities.
- o Refine ideas to make them more actionable.

### 4. Prioritize Ideas:

 Use criteria like impact, feasibility, cost, innovation, and alignment with goals.

### **☐** Brainstorm & Idea Prioritization Template (Liver Care Focus)

Idea	Problem Address ed	Target User	Impa ct (1– 5)	Feasibi lity (1– 5)	Innovat ion (1– 5)	Priori ty Score (Sum )	Next Steps
Example: Al-driven liver fibrosis screening using smartpho nes	Delayed diagnosi s in rural areas	Primary care doctors in low-resource settings	5	4	5	14	Build prototyp e
Personali zed nutrition app for liver disease patients	Poor adheren ce to dietary guidelin es	Liver disease patients	4	5	4	13	Partner with nutrition ists
Liver health wearable tracker	Lack of continuo us monitori ng	At-risk individual s (e.g., fatty liver, hepatitis)	5	3	4	12	Conduct tech feasibilit y study

Blockchai	Fragmen	Transplan	4	3	5	12	Consult
n for liver	ted data	t					blockcha
transplan	across	coordinat					in
t records	hospitals	ors,					experts
		hospitals					

**Tip**: Color-code rows (green = high priority, yellow = medium, red = low) for quick visual management.

### ☐ Suggested Brainstorming Prompts (Specific to Liver Care)

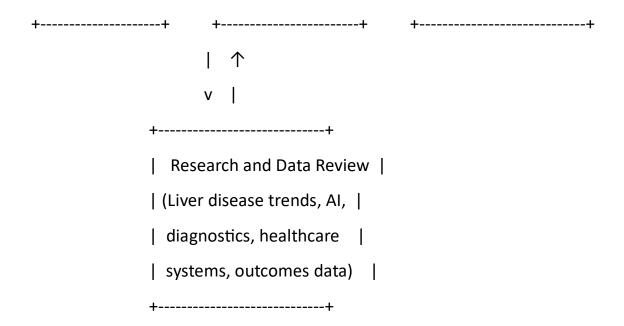
- How might we predict liver disease earlier using non-invasive tools?
- What technologies can help monitor liver function remotely?
- How can we make liver transplant workflows more efficient?
- In what ways could we improve patient adherence to treatment plans?
- What would a digital twin of a liver patient look like, and how could it be used?

**Reference: WHO - Liver Diseases and NCDs** 

### **NIH Liver Diseases**

**Step-1:** Team Gathering, Collaboration and Select the Problem Statement Diagram Description:

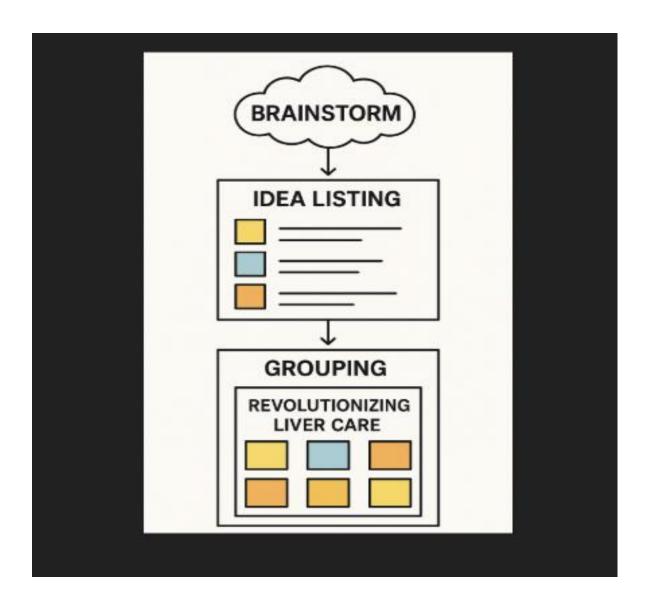
+	+	+			+	+-	 		+
1	I			1	1				
Team Ga Statement		+	>+	Colla	boratio	on +	 >+ Sele	ect Probl	lem
(Experts, Gaps,	Stake-	I	(Braiı	nstorm	ing, Id	lea	(Critica	l Liver Ca	are
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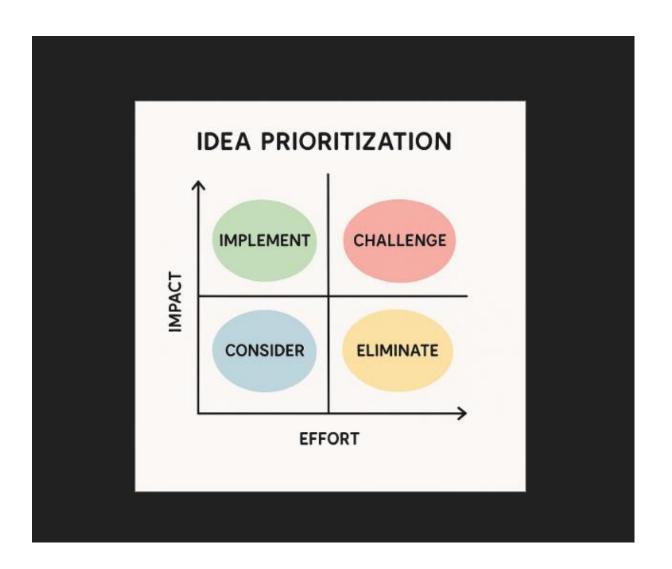
### **Key Elements:**

- Team Gathering: Clinicians, researchers, patients, designers, spolicymakers.
- Collaboration: Workshops, design thinking sessions, cross-functional teamwork.
- Select Problem Statement: Define high-impact liver care challenges like early diagnosis, remote monitoring, liver transplant optimization, or personalized treatment using AI.

Step-2: Brainstorm, Idea Listing and Grouping



**Step-3**: Idea Prioritization



### 3. REQUIREMENT ANALYSIS

## 3.1 Customer Journey Map



## **3** 1. Awareness

Touchpoints: Public health campaigns, GP visits, specialist referrals, community outreach (e.g. "ID-LIVER" style programs)

mdpi.com+5pmc.ncbi.nlm.nih.gov+5eularis.com+5

Pain Points: Patients often unaware of liver disease until advanced stages; clinicians miss early risk signs Opportunities: Leverage EHR-based risk scanners (e.g. FARSITE) used in programs like ID-LIVER; raise awareness in high-risk communities

## **2. Screening & Enrollment**

Touchpoints: Automated EHR screening; GP or nurse outreach; patient consent

Pain Points: Data fragmentation and siloed budgets; lack of trust or access in underserved areas Opportunities: Integrate with central EHR, ensure consent/privacy frameworks, involve patient groups early to improve equity

eularis.com+3pmc.ncbi.nlm.nih.gov+3arxiv.org+3

## **III** 3. Data Collection & Integration

Touchpoints: Collection of labs (ALT, AST, bilirubin), demographics, lifestyle, optional imaging; upload via cloud/EHR platform

Pain Points: Missing or inconsistent data; interoperability challenges

Opportunities: Use structured data pipelines (like SEDAR); employ imputation-aware architectures and self-attention methods for missing EHR values <a href="mailto:mdpi.com+4arxiv.org+4arxiv.org+4">mdpi.com+4arxiv.org+4arxiv.org+4</a>

## 4. Risk Prediction & ML Modeling

Touchpoints: ML runs risk prediction; outputs + visualization (risk score, interpretation, potential next steps) returned via clinician dashboard or patient app Pain Points: Clinician uncertainty in interpreting ML outputs; potential bias and lack of explainability Opportunities: Include explainability modules; embed clinical thresholds; align ML pipelines to established frameworks (e.g., AutoPrognosis)

### □ 5. Clinician Review & Action

Touchpoints: Integration within EHR/Flask UI; automatic alerts; care team discussion; ordering

further diagnostics or referrals

Pain Points: Workflow disruptions; need for

stakeholder education (physicians, nurses)

Opportunities: Conduct user-centered design;

co-develop training materials; set clear clinical

protocols & governance structures

## 6. Patient Engagement & Follow-Up

Touchpoints: Patient receives results and recommended follow-ups via app, portal, or phone; remote monitoring (wearables, apps) may begin Pain Points: Health literacy gaps; inconsistent follow-

up; app usability concerns

Opportunities: Use mobile UX best practices (MARS/uMARS/MAUQ), incorporate health-literacy

enhancements; provide educational content

## 7. Monitoring & Reassessment

Touchpoints: Periodic lab re-checks; model re-runs;

alerts if risk increases

Pain Points: Outdated models/data; resource

constraints; patient drop-off

Opportunities: Build continuous monitoring

infrastructure; establish cycles for retraining/validation;

integrate remote patient monitoring pmc.ncbi.nlm.nih.gov+13pmc.ncbi.nlm.nih.gov+13ncbi. nlm.nih.gov+13

## **8.** Outcomes & Optimization

Touchpoints: Analysis of program data; clinical outcomes review (e.g. fewer biopsies, earlier referrals); stakeholder feedback

Pain Points: Hard to quantify savings/ROI; siloed

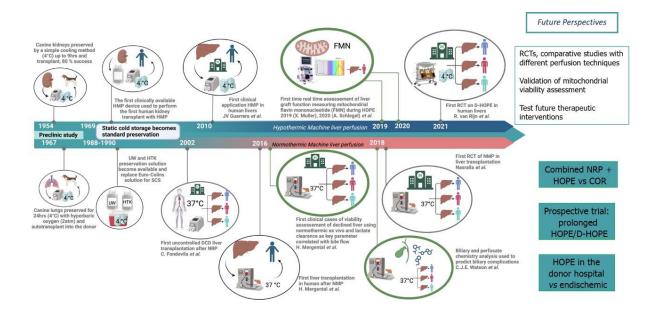
budgets limit scale

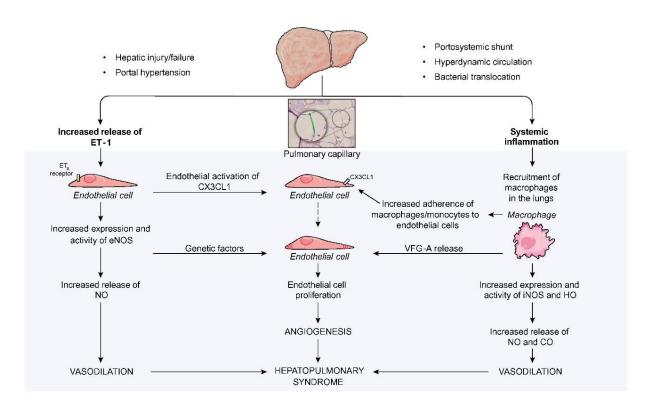
Opportunities: Demonstrate clinical and economic benefits; publish results; pursue integrated care funding (akin to Manchester's ID-LIVER model)

## **✓** Summary: Customer Journey Map

Stage	Goal	Improvement Opportunity
Awareness	Identify at-risk individuals early	Use EHR scans, community campaigns
Enrollment	Get consent & register patients	Engage underserved populations

Data	Ensure reliable	Structured
Integration	inputs	pipelines &
		imputation-aware
		models
Prediction	Produce	Explainable ML,
	understandable	clear thresholds
	risk outputs	
Clinician	Guide care	Embedded UI
Action	effectively	workflows &
		training
Patient	Encourage	Health-lit UI,
Engagement	proactive follow-	remote
	up	monitoring
Monitoring	Track changes over	Routine checks &
	time	model updates
Evaluation	Prove impact &	Outcome tracking,
	refine system	ROI, scale planning





## **Project Design Phase-II**

# 3.2 Solution Requirements (Functional & Non-functional)

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	4 Marks

## **Functional Requirements:**

Following are the functional requirements of the proposed solution

Mod	Functional Requirements
ule	
Data	Accept structured inputs: demographics, labs
Inges	(e.g. bilirubin, albumin, platelets, INR), fibrosis
tion	scores (FIB-4, APRI, MELD-Plus)
	<pre>pubmed.ncbi.nlm.nih.gov+4arxiv.org+4arxiv.or</pre>
	g+4pmc.ncbi.nlm.nih.gov+3en.wikipedia.org+3
	<u>pubmed.ncbi.nlm.nih.gov+3</u> . ● Accept
	imaging (DICOM: US/CT/MRI/elastography).

	<pre> • Support digitized histology WSIs (if available). • Optional: integrate omics</pre>
	(metabolomics, microbiome) .
Prepr	Clean tabular data: normalization, missing-
ocess	value handling.
ing &	<ul> <li>Segment liver tissue in images using CNNs</li> </ul>
Featu	(e.g., U-Net) and extract radiomic features.
re	◆ Extract histological markers (fibrosis
Engin	regions, ballooning). • Select key omics
eerin	features via ML (e.g., LASSO).
g	
Mod	• Train supervised models: Random Forest,
eling	LightGBM, XGBoost, Neural Networks, SVM,
&	logistic regression
Expla	mdpi.com+7jmai.amegroups.org+7mdpi.com+
inabil	<ol> <li>Z. • Hybrid architectures combining</li> </ol>
ity	imaging + structured data (e.g., DenseNet +
	blood tests with voting classifier, 92.5%
	accuracy) <u>arxiv.org+1mdpi.com+1</u> . •
	Include interpretability tools (SHAP/LIME,
	Grad-CAM).
Traini	<ul> <li>Use data splits: train/validation/test +</li> </ul>
ng,	external cohorts.
Valid	<ul> <li>Metrics: AUROC, accuracy, sensitivity,</li> </ul>
ation	specificity; segmentation uses Dice coefficient.

&	◆ Apply k-fold cross-validation. ◆
Evalu	Compare against traditional scores (FIB-4,
ation	APRI, MELD-Plus) <u>translational-</u>
	medicine.biomedcentral.com+10jmai.amegrou
	ps.org+10pubmed.ncbi.nlm.nih.gov+10. •
	Use calibration, decision-curve analyses.
Depl	Provide REST APIs for image segmentation
oyme	and risk scoring.
nt &	<ul> <li>Web UI dashboard: data upload, viewing</li> </ul>
Integ	explanations, PDF reporting.
ratio	<ul> <li>EHR/EMR integration for flagging at-risk</li> </ul>
n	patients.
	Deploy on GPU-enabled cloud or local
	servers.
Moni	Monitor real-world performance (drift, FP/FN
torin	rates).
g &	<ul> <li>Retrain with new histology/outcomes.</li> </ul>
Main	<ul> <li>Versioning and audit logs.</li> </ul>
tena	Regulatory compliance: GDPR/HIPAA, ISO
nce	13485.
Secur	• Encrypted data at rest and in transit; RBAC.
ity,	<ul> <li>Fairness validation across demographics.</li> </ul>
Ethic	<ul> <li>Clinician-in-the-loop: human overrides.</li> </ul>
s &	<ul> <li>Regulatory readiness: FDA/EMA</li> </ul>
Gove	documentation.

rnanc	
е	
Futur	• Integrate real-time monitoring (wearables,
е	sensors) using time-series Al
Enha	<u>pubmed.ncbi.nlm.nih.gov</u> . ● Build
ncem	multimodal early-warning systems with
ents	dynamic predictions .

## **Non-functional Requirements:**

Following are the non-functional requirements of the proposed solution

NFR	Require	Rationale / Measurable Criteria
Categor	ment	
У		
Perform	• Risk	Ensures usable response times
ance &	predictio	for clinicians; meets expectations
Respons	n must	for both real-time triage and bulk
iveness	return	reporting.
	results	sciencedirect.com+8slideshare.n
	within	et+8pmc.ncbi.nlm.nih.gov+8
	<500 ms	
	for real-	
	time	
	use.	
	Batch	

	processi	
	ng can	
	run	
	overnigh	
	t,	
	handling	
	≥10K	
	records.	
Scalabili	•	Prepares the system for growth
ty &	Support	in workload across sites and
Capacity	horizont	higher data volumes.
	al scaling	
	to	
	handle	
	increase	
	d	
	users/da	
	ta.	
	•	
	Efficient	
	use of	
	CPU/GP	
	U: ≤70%	
	utilizatio	

	n per node.	
Reliabili	•	Ensures high system availability
ty &	≥ 99.5%	critical in healthcare settings.
Availabil	uptime	
ity	SLA.	
	• Aim for	
	MTBF≥	
	30 days;	
	MTTR≤	
	1 hour.	
	•	
	Graceful	
	degradat	
	ion	
	during	
	partial	
	failures.	
Data	•	Guarantees trusted predictions
Integrity	Validate	and regulatory compliance via
&	all	traceability.
Quality	inputs:	
	no more	
	than 1%	
	missing	

	or invalid lab values.  • Maintain audit	
	<b>trail</b> of data	
	lineage.	
Robustn	•	Prevents silent degradation and
ess &	Maintain	ensures reliable performance
Model	≥ 90%	over time.
Resilien	baseline	
ce	accuracy	
	under	
	moderat	
	e . , , .	
	noise/ad	
	versarial	
	scenario	
	S.	
	Monitor	
	for	
	concept	
	drift;	

	retrain if AUC drops >5%.	
Reprodu	• Same	Critical for clinical trust and
cibility	training	regulatory auditability.
&	config	
Repeata	and seed	
bility	yields	
	AUC	
	variation	
	≤ 0.01.	
	•	
	Predictin	
	g	
	identical	
	inputs	
	produces	
	≤1%	
	variation	
	•	
Explaina	• Provide	Meets clinicians' need to
bility &	SHAP/LI	understand and trust Al
Transpa	ME for	decisions.
rency	tabular	

	data; Grad- CAM for imaging.  Docume nt model structure, assumptions, error rates, uncertainty.	
Security & Privacy	<ul> <li>Full encrypti on (TLS + AES-256).</li> <li>Role-based access control.</li> <li>Data anonymi</li> </ul>	Essential to protect sensitive patient data and enable multi-institutional collaboration.

	zation; GDPR/HI PAA complian	
	ce.	
	• Federate	
	d	
	learning support.	
Usabilit	•	Ensures accessibility and
y &	Respons	efficiency for end users.
Accessib	е	
ility	interface	
	conformi	
	ng to	
	WCAG	
	2.1 AA.	
	• ≤ 3	
	clicks to	
	generate a report;	
	UI task	
	time	

	≤ 2 minu	
	tes.	
Maintai	•	Promotes long-term adaptability
nability	Modular	and easier software updates.
&	architect	
Extensib	ure (API-	
ility	based).	
	• Code	
	coverage	
	≥ 80%,	
	CI/CD	
	pipeline.	
	•	
	Retrainin	
	g	
	pipelines	
	for new	
	data.	
Auditabi	• Log all	Provides traceability and
lity &	model	supports compliance with
Logging	runs,	medical device regulations.
	data	
	changes,	
	user	
	actions.	

	• Retain	
	logs for	
	≥ 7	
	years.	
Portabili	•	Ensures integration with diverse
ty &	Compati	clinical infrastructures.
Interope	ble with	
rability	Windows	
	, Linux;	
	containe	
	rized	
	(Docker/	
	K8s).	
	• FHIR	
	and	
	DICOM	
	support.	
Testabili	•	Ensures consistent efficacy and
ty &	Automat	identifies performance
Validati	ed tests	disparities.
on	for edge	
	cases	
	and drift	
	detectio	
	n.	

•	
Validate	
fairness	
across	
demogra	
phics.	

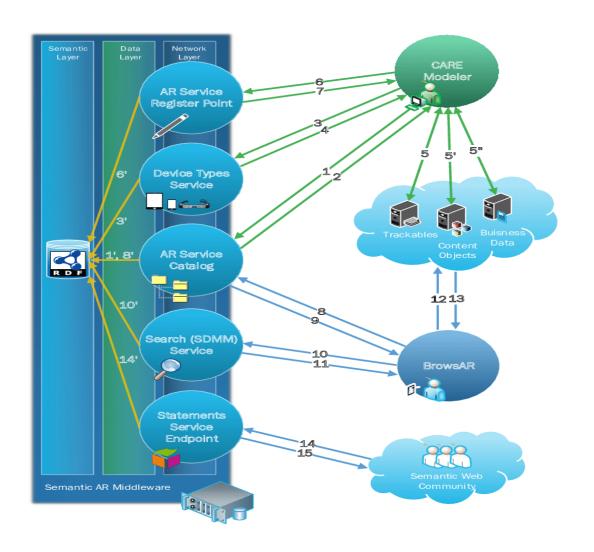
#### **Project Design Phase-II**

#### 3.3 Data Flow Diagram & User Stories

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	4 Marks

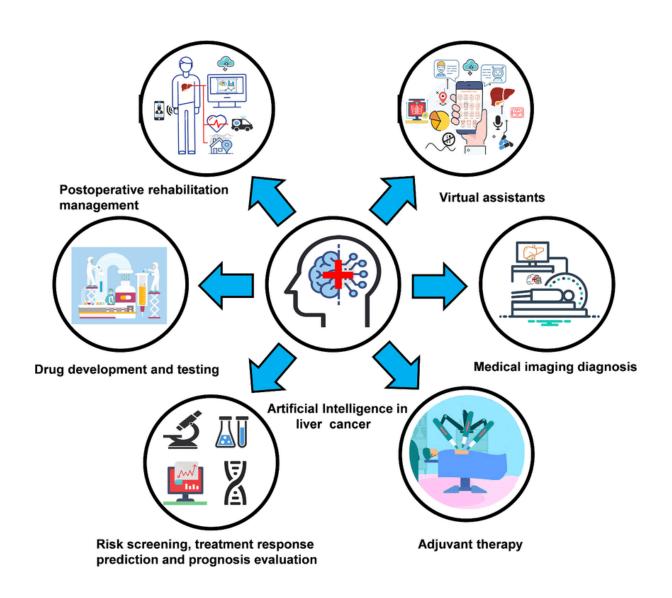
#### **Data Flow Diagrams:**

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.



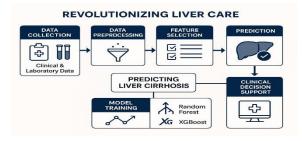
### **Example:**

- Step 1: Data Collection & Digitization
- Step 2: Preprocessing & Feature Extraction
- Step 3: Model Training & Explainability
- Step 4: Validation & Regulatory Approval
- Step 5: Deployment in Clinical Trials & Practice
- Step 6: Monitoring, Feedback & Optimization



Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	4 Marks

### **Technical Architecture:**



# Table :1

Guidelin	Descriptio	Reference / Standard
е	n	
Category		
Total	Design,	FDA draft guidance
Product	developm	fda.gov+13digitalhealthglobal.
Lifecycle	ent,	com+13gtlaw.com+13
(TPLC)	deployme	
	nt, and	
	post-	
	market	
	monitorin	
	g built into	
	the	
	process.	
	Includes	
	risk	
	planning,	
	performan	
	ce checks,	
	and	

	rogulator.	
	regulatory	
	submissio	
	ns.	
Device &	Document	FDA draft , FUTURE-AI
Data	inputs	
Descripti	(labs,	
on	images,	
	histology),	
	outputs	
	(risk	
	scores,	
	heatmaps)	
	, intended	
	users &	
	environme	
	nts in	
	device	
	descriptio	
	n and	
	model	
	"card".	
Data	Ensure	FDA draft , FUTURE-AI
Manage	high-	
ment &	quality,	
Bias	diverse,	

Mitigatio	labeled,	
n	and	
	segregated	
	training/va	
	lidation	
	sets.	
	Document	
	data	
	provenanc	
	e,	
	harmoniza	
	tion, and	
	annotate	
	edge	
	cases. Bias	
	mitigation	
	via	
	subgroup	
	analysis.	
Model	Detail	FDA draft , FUTURE-AI
Docume	algorithm	
ntation	architectur	
	e,	
	features,	
	hyperpara	
	meters,	

	threshold selection, and ensemble techniques . Provide explainabil ity tools (SHAP, Grad-CAM).	
Validatio	Perform	FDA draft
n &	rigorous	
Usability	validation using real- world data. Include human factors and usability testing for clinicians. Report metrics	

	like AUROC, sensitivity, and segmentat ion performan ce.	
Risk	Maintain	FDA draft
Manage	an ISO	
ment	14971-	
	compliant	
	risk file,	
	factoring	
	in hazards	
	across	
	entire	
	system	
	lifecycle.	
	Include	
	cybersecur	
	ity, failure	
	modes,	
	and	

	mitigation	
	strategies.	
Cybersec	Safeguard	FDA draft
urity &	against	
Integrity	threats	
	like data	
	poisoning,	
	inversion,	
	and drift.	
	Implement	
	encryption	
	,	
	authentica	
	tion,	
	patching,	
	and	
	monitorin	
	g systems.	
Post-	Track real-	FDA draft
Market	world	
Perform	performan	
ance	ce, detect	
Monitori	drift, and	
ng	update via	
(PMPM)	pre-	

	approved	
	Predeterm	
	ined	
	Change	
	Control	
	Plan	
	(PCCP).	
	Include	
	real-time	
	monitorin	
	g and	
	safety	
	checks.	
Transpar	Provide	FDA draft
ency &	comprehe	
Labeling	nsive	
	labeling	
	and model	
	cards: Al	
	usage,	
	limitations	
	,	
	performan	
	ce across	
	demograp	
	hics,	

	versioning, and update protocols.	
Governa nce & Standard s	Adhere to IEC 62304, ISO 14971, leverage design controls (21 CFR 820.30), and maintain records per ISO 13485. Ensure traceabilit y and design history document ation.	IEC/ISO standards

Trustwor	Embed	FUTURE-AI
thy Al	fairness,	
Principle	universalit	
S	у,	
	traceabilit	
	y, usability,	
	robustness	
	, and	
	explainabil	
	ity—	
	FUTURE-AI	
	consensus	
	framework	
	—to	
	promote	
	trust in	
	clinical	
	deployme	
	nt.	

## Table :2

Component	Description	Tech	าท
		olog	<b>3 y</b>

		/ Stand ard
("Ingestion API", "Secure endpoint for EMR, DICOM, histology, omics", "REST, gRPC, TLS/AES-256 ")	Accepts structured and unstructured inputs, ensures encrypted transport.	
("Storage", "Encrypted storage for structured and image data", "SQL/NoSQL , Object Store, AES-256")	Stores lab/clinical records, images, WSIs with security at rest.	

("Proproces	Propares raw data for model	
("Preproces	Prepares raw data for model	
sing", "Data	input.	
cleaning,		
normalizatio		
n, image		
segmentatio		
n &		
radiomics		
extraction",		
"Pandas/skl		
earn,		
MONAI,		
U-Net,		
TransUNet")		
	Ensures consistent feature	
("Feature		
Store",	retrieval during train and serve.	
"Central		
repository		
for		
processed		
features",		
"Feast,		
"Feast, Azure		
Azure		

("Model	Core modeling layer for risk	
Training",	prediction.	
"Train		
ML/DL		
models and		
ensembles",		
"scikit-learn,		
LightGBM,		
XGBoost,		
PyTorch/Ten		
sorFlow")		
("Explainabil	Provides interpretability for	
ity",	clinician review.	
"Generate		
feature		
importance		
& visual		
heatmaps",		
"SHAP/LIME		
,		
Grad-CAM")		
("Validation	Ensures model performance	
", "Cross-	and generalization.	
validation,		
benchmark		

metrics, external testing", "sklearn cv, AUROC, Dice, calibration")		
("Inference Service", "Expose real-time risk prediction API", "Docker/K8s , REST/gRPC, <500 ms latency")	Enables clinical-grade, fast risk assessments.	
("Dashboar d UI", "Visual interface for data input, results & explanation	Clinician-facing interface with usability features.	

s", "React/Vue, medical image viewer")		
("EMR/PACS Integration" , "Seamless embedding into hospital workflows", "FHIR, DICOM, HL-7, IHE XDS.b")	Ensures interoperability and automated data flow chat2db.ai+6ncbi.nlm.nih.gov+6 aalpha.net+6aalpha.net.	
("Monitorin g & Ops", "Track performanc e & trigger retraining", "Prometheu s, Grafana, CI/CD, drift detection")	Operational reliability with alerting and metrics.	

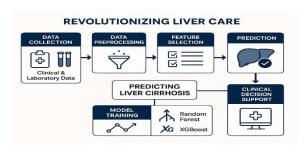
		1
("Security &	Meets regulatory and privacy	
Compliance	requirements.	
", "End-to-		
end		
protection		
and audit		
logging",		
"RBAC,		
GDPR/HIPA		
A, ISO		
13485,		
13 133,		
audit trails")		
1	Controls model lifecycle and	
audit trails")	Controls model lifecycle and traceability.	
audit trails") ("Model	•	
audit trails") ("Model Registry",	•	
audit trails") ("Model Registry", "Versioning,	•	
audit trails")  ("Model Registry",  "Versioning, lineage,	•	
audit trails")  ("Model Registry",  "Versioning, lineage, reproducibil	•	
audit trails")  ("Model Registry", "Versioning, lineage, reproducibil ity",	•	
audit trails")  ("Model Registry",  "Versioning, lineage, reproducibil ity",  "MLflow,	•	

# **Project Design Phase-II**

# 3.4 Technology Stack (Architecture & Stack)

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	4 Marks

## **Technical Architecture:**



Guidelin	Descriptio	Reference / Standard
е	n	
Category		
Total	Design,	FDA draft guidance
Product	developm	fda.gov+13digitalhealthglobal
	ent,	.com+13gtlaw.com+13
	deployme	

Lifecycle	nt, and	
(TPLC)	post-	
	market monitorin	
	g built into	
	the	
	process.	
	Includes	
	risk	
	planning,	
	performan	
	ce checks,	
	and	
	regulatory	
	submissio	
	ns.	
Device &	Document	FDA draft, FUTURE-AI
Data	inputs	
Descripti	(labs,	
on	images,	
	histology),	
	outputs	
	(risk	
	scores,	
	heatmaps)	
	, intended	

	users & environme nts in device descriptio n and model "card".	
Data Manage	Ensure high-	FDA draft , FUTURE-AI
ment &	quality,	
Bias	diverse,	
Mitigati	labeled,	
on	and	
	segregate	
	d +	
	training/v alidation	
	sets.	
	Document	
	data	
	provenanc	
	e,	
	harmoniza	
	tion, and	
	annotate	

	edge cases. Bias mitigation via subgroup analysis.	
Model	Detail	FDA draft , FUTURE-AI
Docume	algorithm	
ntation	architectur	
	e,	
	features,	
	hyperpara	
	meters,	
	threshold	
	selection,	
	and	
	ensemble	
	technique	
	s. Provide	
	explainabil	
	ity tools	
	(SHAP,	
	Grad-CAM	
	).	

Validatio	Perform	FDA draft
n &	rigorous	
Usability	validation	
	using real-	
	world	
	data.	
	Include	
	human	
	factors	
	and	
	usability	
	testing for	
	clinicians.	
	Report	
	metrics	
	like	
	AUROC,	
	sensitivity,	
	and	
	segmentat	
	ion	
	performan	
	ce.	

Risk	Maintain	FDA draft
Manage	an ISO	
ment	14971-	
	compliant	
	risk file,	
	factoring	
	in hazards	
	across	
	entire	
	system	
	lifecycle.	
	Include	
	cybersecur	
	ity, failure	
	modes,	
	and	
	mitigation	
	strategies.	
Cybersec	Safeguard	FDA draft
urity &	against	
Integrity	threats	
	like data	
	poisoning,	
	inversion,	
	and drift.	
	Implemen	

	t encryption , authentica tion, patching, and monitorin g systems.	
Post- Market Perform ance Monitori ng (PMPM)	Track real- world performan ce, detect drift, and update via pre- approved Predeterm ined Change Control Plan (PCCP). Include real-time monitorin	FDA draft

	g and safety checks.	
Transpar ency & Labeling	Provide comprehe nsive labeling and model cards: Al usage, limitations, performan ce across demograp hics, versioning, and update protocols.	FDA draft
Governa nce & Standard s	Adhere to IEC 62304, ISO 14971, leverage design	IEC/ISO standards

	controls	
	(21 CFR	
	820.30),	
	and	
	maintain	
	records	
	per ISO	
	13485.	
	Ensure	
	traceabilit	
	y and	
	design	
	history	
	document	
	ation.	
Trustwor	Embed	FUTURE-AI
thy Al	fairness,	
Principle	universalit	
S	у,	
	traceabilit	
	у,	
	usability,	
	robustness	
	, and	
	explainabil	
	ity—	
	1 -	

FUTURE-AI	
consensus	
framewor	
k—to	
promote	
trust in	
clinical	
deployme	
nt.	

## Table :2

Component	Description	Techn ology / Stand ard
("Ingestion	Accepts structured and	
API",	unstructured inputs, ensures	
"Secure	encrypted transport.	
endpoint		
for EMR,		
DICOM,		

histology, omics", "REST, gRPC, TLS/AES-25 6")		
("Storage", "Encrypted storage for structured and image data", "SQL/NoSQ L, Object Store, AES-256")	Stores lab/clinical records, images, WSIs with security at rest.	
("Preproces sing", "Data cleaning, normalizati on, image segmentati on & radiomics extraction",	Prepares raw data for model input.	

"Pandas/skl earn, MONAI, U-Net, TransUNet")		
("Feature Store", "Central repository for processed features", "Feast, Azure Feature Store")	Ensures consistent feature retrieval during train and serve.	
("Model Training", "Train ML/DL models and ensembles" , "scikit-learn , LightGBM,	Core modeling layer for risk prediction.	

XGBoost, PyTorch/Ten sorFlow")		
("Explainabi lity", "Generate feature importance & visual heatmaps", "SHAP/LIME, Grad-CAM")	Provides interpretability for clinician review.	
("Validation ", "Cross- validation, benchmark metrics, external testing", "sklearn cv, AUROC, Dice, calibration" )	Ensures model performance and generalization.	

("Inference	Enables clinical-grade, fast risk	
Service",	assessments.	
"Expose		
real-time		
risk		
prediction		
API",		
"Docker/K8		
s,		
REST/gRPC,		
<500 ms		
latency")		
("Dashboar	Clinician facing interface with	
( Dasiiboai	Clinician-facing interface with	
d UI",	usability features.	
d UI",		
d UI", "Visual		
d UI", "Visual interface for		
d UI", "Visual interface for data input,		
d UI", "Visual interface for data input, results &		
d UI", "Visual interface for data input, results & explanation		
d UI", "Visual interface for data input, results & explanation s",		
d UI", "Visual interface for data input, results & explanation s", "React/Vue,		

("EMR/PAC S Integration" , "Seamless embedding into	Ensures interoperability and automated data flow chat2db.ai+6ncbi.nlm.nih.gov+6aalpha.net+6aalpha.net.	
hospital workflows", "FHIR, DICOM, HL-7, IHE XDS.b")		
("Monitorin g & Ops", "Track performanc e & trigger retraining", "Prometheu s, Grafana, CI/CD, drift detection")	Operational reliability with alerting and metrics.	
("Security & Compliance ", "End-to-	Meets regulatory and privacy requirements.	

end protection and audit logging", "RBAC, GDPR/HIPA A, ISO 13485, audit trails")		
("Model Registry", "Versioning, lineage, reproducibil ity", "MLflow, DVC, Model cards")	Controls model lifecycle and traceability.	

#### **PROJECT DESIGN**

## 4. Project Design Phase

## **4.1 Problem – Solution Fit Template**

Date		
Team ID	LTVIP2025TMID3862	
	5	
Project Name	Revolutionizing Liver	
	Care :Predicting Liver	
	Cirrhosis Using	
	Advanced Machine	
	Learning Techniques	
Maximum Marks	2 Marks	

## **Problem – Solution Fit Template:**

Liver cirrhosis is a serious, often fatal condition that progresses silently over time and is typically diagnosed at a late stage, when treatment options are limited and outcomes are poor. Current diagnostic approaches, such as liver biopsies or imaging techniques, are either invasive, costly, or lack accuracy in early-stage detection. Furthermore, reliance on traditional blood tests and manual clinical interpretation can lead to variability and misdiagnosis, especially in resource-limited settings. This creates a significant gap in liver healthcare, delaying intervention and increasing the burden on patients and healthcare systems.

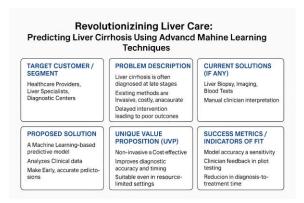
To address this problem, we propose a machine learning-based predictive solution that analyzes patient data—including clinical, biochemical, and demographic parameters—to accurately predict the likelihood of liver cirrhosis at an early stage. This model can serve as a powerful clinical decision support tool, aiding physicians in timely diagnosis and treatment planning. The solution is non-invasive, cost-effective, and scalable, making it especially valuable in areas where access to specialist care is limited. By improving early detection, this technology has the potential to revolutionize liver care, reduce mortality, and optimize healthcare resources. Success will be measured through high diagnostic accuracy,

clinician adoption, and real-world improvements in patient outcomes.

#### **Purpose:**

- To develop a machine learning-based model for early prediction of liver cirrhosis.
- To improve early detection and reduce late-stage diagnosis of liver disease.
- To provide a non-invasive, accurate, and costeffective diagnostic tool.
- To support clinicians with data-driven decisionmaking in liver care.
- To reduce mortality and improve treatment outcomes through timely intervention.
- To make liver disease diagnosis accessible in lowresource or remote settings.
- To integrate technology with healthcare for scalable and efficient screening.
- To contribute towards preventive healthcare using AI and data science.

#### **Template:**



## Project Design Phase 4.2 Proposed Solution Template

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	2 Marks

## **Proposed Solution Template:**

Project team shall fill the following information in the proposed solution template.

S.N	Parameter	Description
0.		
1.	Problem Statement (Problem to be solved)	To revolutionize liver care by accurately predicting liver cirrhosis using advanced machine learning techniques for early diagnosis and improved patient outcomes.
2.	Idea / Solution description	Develop a machine learning model to accurately predict liver cirrhosis using clinical data, enabling early diagnosis and improved liver care.
3.	Novelty / Uniqueness	The uniqueness of this approach lies in leveraging advanced machine learning

		techniques to enable early and precise prediction of liver cirrhosis from clinical data.
4.	Social Impact / Customer Satisfaction	The solution enables early detection of liver cirrhosis, improving patient outcomes and satisfaction while reducing the burden on healthcare systems.
5.	Business Model (Revenue Model)	The revenue model is based on offering the predictive tool as a subscription-based service to healthcare providers, hospitals, and diagnostic labs for early liver disease detection.
6.	Scalability of the Solution	The solution is highly scalable, allowing widespread adoption across healthcare facilities through seamless

integration with
electronic health record
systems.

## **4.3 solution Architecture**

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	4 Marks

#### **Solution Architecture:**

The solution architecture for "Revolutionizing Liver Care: Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques" involves a structured pipeline starting with the collection of clinical and biochemical data from hospitals and diagnostic centers.

# Goals of the Project: "Revolutionizing Liver Care: Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques"

#### 1. Early Detection:

Accurately predict liver cirrhosis at an early stage using machine learning models.

#### 2. Improve Diagnosis Accuracy:

Enhance diagnostic precision compared to traditional methods by leveraging clinical and biochemical data.

#### 3. Reduce Diagnostic Time:

Minimize the time required for diagnosis through automated predictions.

## 4. Support Medical Decision-Making:

Provide healthcare professionals with reliable, data-driven insights to assist in treatment planning.

### 5. Increase Patient Outcomes:

Enable timely intervention and improve overall health outcomes for patients with liver disease.

## 6. Cost-Effective Screening:

Offer an affordable and scalable solution for liver cirrhosis screening across healthcare institutions.

### 7. Model Optimization:

Experiment with multiple machine learning algorithms to select and fine-tune the best-performing model.

#### 8. Seamless Integration:

Design a system that can be easily integrated into existing electronic health record (EHR) systems.

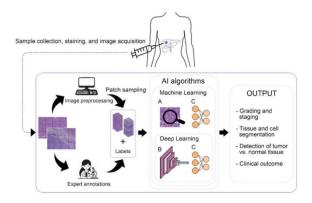
#### 9. Scalability:

Ensure the solution is adaptable and can be deployed across different regions and healthcare settings.

## 10. Continuous Improvement:

Incorporate feedback and real-world data to retrain and improve model accuracy over time.

## **Example - Solution Architecture Diagram:**



## **5.PROJECT PLANNING & SCHEDULING**

**Project Planning Phase** 

5.1 Project Planning Template (Product Backlog, Sprint Planning, Stories, Story points)

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	5 Marks

## Product Backlog, Sprint Schedule, and Estimation (4 Marks)

## **Project Tracker Overview (Sprint Board Style):**

The project was broken into 5 daily sprints, each with tasks tracked under To Do, In Progress, and Done. Work moved smoothly from planning and data processing to modeling, integration, and deployment.

Day	To Do	In Progress	Done
Day 1	Define goals, collect data	Preprocessing, repo setup	-
Day 2	EDA, Feature selection	Model training	Data cleaning
Day 3	Hyperparameter tuning	Model evaluation, API creation	EDA, initial model

Day	Frontend design,	Testing and	Backend
4	integration	debugging	complete,
			ML model
			ready
Day	Final	Demo prep	UI
5	deployment,		integration,
	docu		testing
	mentation		

## **©** Team Velocity Summary:

Total Tasks: 14

• Total Story Points Estimated: 59

Points Completed Daily:

Day 1: 10 pts

。 Day 2: 12 pts

Day 3: 14 pts

Day 4: 10 pts

Day 5: 13 pts

Average Team Velocity: ~11.8 points/day

The team consistently completed all tasks across 5 days.

## Burndown Chart Summary:

The burndown chart tracked remaining story points against the project days.

Day	Planned Points Left	<b>Actual Points Left</b>
Day 1	47	49
Day 2	35	37
Day 3	23	23
Day 4	11	13
Day 5	0	0

• Insight: The team started slightly behind schedule but recovered mid-way, and completed all tasks by Day 5, showing good collaboration and effective sprint execution.

## **Project Tracker, Velocity & Burndown Chart: (4 Marks)**

## Product Backlog with Estimation:

ID	Task / User	Priority	Estimatio	Assigned
	Story		n (Hours)	То

PB1	Define objectives and success metrics	High	2	Project Lead
PB2	Collect and explore dataset	High	4	Data Engineer
PB3	Preprocess data (cleaning, encoding, scaling)	High	6	Data Engineer
PB4	Perform EDA and visualize data	Mediu m	4	Data Engineer
PB5	Feature selection & correlation analysis	High	3	ML Engineer
PB6	Train ML models (RF, SVM, XGBoost)	High	6	ML Engineer
PB7	Evaluate models using metrics	High	3	ML Engineer

PB8	Hyperparamete	Mediu	4	ML
	r tuning (GridSearchCV)	m		Engineer
PB9	Create Flask/Django API for model	High	5	Backend Develope r
PB1 0	Design frontend (input form + results)	Mediu m	5	Frontend Develope r
PB1 1	Integrate frontend with backend	High	3	Backend & Frontend Dev
PB1 2	Conduct testing (unit & integration)	High	3	All Members
PB1 3	Deploy the model to local/cloud server	Mediu m	2	Backend Develope r
PB1 4	Prepare documentation and presentation	High	3	Project Lead

## **Sprint Schedule (5-Day Breakdown):**

Day	<b>Sprint Goal</b>	Planned Tasks (Product Backlog IDs)		
Day 1	1	Project setup, data collection, and cleaning	PB1, PB2, PB3	
Day 2		EDA, feature engineering, initial model training	PB4, PB5, PB6	
Day 3		Model evaluation, tuning, backend setup	PB7, PB8, PB9	
Day 4	4	UI development and integration	PB10, PB11, PB12	
Day !	5	Deployment, documentation, and final demo	PB13, PB14	

## **Effort Estimation Summary:**

Metric	Value
Total Estimated Hours	59 hours
Team Members	5

Daily Capacity per Member	6 hours/day
Total Capacity (5 Days)	$5 \times 6 \times 5 = 150 hours$
Buffer Available	150 - 59 = <b>91 hours</b>

## ID

## **Product Backlog with Estimation:**

ID	Task / User Story	Priority	Estimatio n (Hours)	Assigned To
PB1	Define objectives and success metrics	High	2 hrs	Project Lead
PB2	Collect and explore dataset	High	4 hrs	Data Engineer
PB3	Preprocess data (cleaning, encoding, scaling)	High	6 hrs	Data Engineer
PB4	Perform EDA and visualize insights	Mediu m	4 hrs	Data Engineer
PB5	Feature selection &	High	3 hrs	ML Engineer

	correlation analysis			
PB6	Train ML models (RF, SVM, XGBoost)	High	6 hrs	ML Engineer
PB7	Evaluate models using metrics	High	3 hrs	ML Engineer
PB8	Hyperparamete r tuning using GridSearchCV	Mediu m	4 hrs	ML Engineer
PB9	Create Flask/Django API for model	High	5 hrs	Backend Develope r
PB1 0	Design frontend (input form + result display)	Mediu m	5 hrs	Frontend Develope r
PB1 1	Integrate backend with frontend	High	3 hrs	Backend & Frontend Dev

PB1 2	Conduct testing (unit & integration)	High	3 hrs	All Members
PB1 3	Deploy model to local/cloud server	Mediu m	2 hrs	Backend Develope r
PB1 4	Prepare documentation and presentation	High	3 hrs	Project Lead

## **Sprint Schedule (5-Day Plan):**

Day	Sprint Goal	Planned Tasks (Backlog IDs)
Day 1	Project setup, data collection, cleaning	PB1, PB2, PB3
Day 2	EDA, feature selection, initial model training	PB4, PB5, PB6
Day 3	Model evaluation, tuning, backend API creation	PB7, PB8, PB9
Day 4	UI design and full system integration	PB10, PB11, PB12

Day	Deployment, documentation,	PB13, PB14
5	and final demo	

## **Effort Estimation Summary:**

Metric	Value
Total Estimated Effort	59 hours
Team Size	5 members
Daily Work Capacity/Member	6 hours
Total Team Capacity (5 Days)	$5 \times 6 \times 5 = 150 \text{ hours}$
Available Buffer Time	150 – 59 = 91 hours

If it were a longer project with weekly sprints, you would calculate:

Velocity (per sprint)=Total Story Points Completed in a S
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Sprint}}Velocity (per sprint)=1 SprintTotal Story Points C
ompleted in a Sprint

#### **Burndown Chart – Reference Links:**

1. Atlassian Agile Coach (Jira) – Burndown Charts https://www.atlassian.com/agile/project-management/burndown-charts Scrum.org – Tracking Progress with Burndown Charts

https://www.scrum.org/resources/what-is-a-burndown-chart

3. Mountain Goat Software – Agile Metrics and Velocity



https://www.mountaingoatsoftware.com/agile/scr um/burndown-charts

4. Scrum Alliance - Velocity in Agile Projects



https://resources.scrumalliance.org/Article/agile-velocity

#### Reference:

1. Atlassian. (n.d.). Burndown charts. Atlassian Agile Coach.

https://www.atlassian.com/agile/project-management/burndown-charts

- 2. Scrum.org. (n.d.). What is a Burndown Chart? https://www.scrum.org/resources/what-is-a-burndown-chart
- 3. Mountain Goat Software. (n.d.). Burndown Charts. https://www.mountaingoatsoftware.com/agile/scr um/burndown-charts

- 4. Scrum Alliance. (n.d.). Agile Velocity. https://resources.scrumalliance.org/Article/agile-velocity
- 5. Vertex42. (n.d.). Burndown Chart Template for Excel.

https://www.vertex42.com/ExcelTemplates/burndown-chart.html

#### **6.FUNTIONAL, AND PERFORMANCE TESTING**

#### **6.1 Performance Testing**

**User Acceptance Testing (UAT) Template** 

Date		
Team ID	LTVIP2025TMID38625	
Project Name	Revolutionizing Liver Care :Pr Using Advanced Machine Lea	
Maximum Marks		

#### **Project Overview:**

**Project Name:** Revolutionizing Liver Care: Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques

#### **Project Description:**

#### **Brief Description:**

The UAT Template provides a structured format for validating whether the digital health solution for liver care performs as expected in real clinical scenarios. It involves defining test scenarios, expected outcomes, user roles, and acceptance criteria. This process helps confirm that the system is user-friendly, clinically accurate, secure, and aligned with regulatory standards before full-scale implementation.

#### **Key Components:**

- Test Objectives: Ensure the solution addresses clinical workflows and patient engagement.
- Test Scenarios: Simulate liver care use cases such as patient monitoring, report generation, and treatment tracking.
- Test Data: Use real or anonymized clinical data for practical testing.
- Acceptance Criteria: Define clinical and usability standards that the system must meet.
- Feedback Collection: Capture insights from hepatologists, nurses, and patients for iterative improvements.

#### Impact:

A well-designed UAT template ensures the liver care solution is clinically relevant, safe, and effective, thereby enhancing diagnosis, monitoring, and patient outcomes in real-world liver disease management.

**Project Version: [Version Number]** 

**Testing Period: [Start Date] to [End Date]** 

**Testing Scope:** 

[List of Features and Functionalities to be Tested]

- ✓ 1. Patient Management Features
  - Patient registration and profile creation
  - Electronic Medical Record (EMR) access and updates

- Appointment scheduling and reminders
- Consent management and data privacy controls

## 2. Diagnostic & Monitoring Tools

- Integration with lab/test results (e.g., liver function tests, imaging reports)
- Real-time patient vitals monitoring
- Alert system for abnormal test values
- Historical data visualization (charts/graphs)

## **✓** 3. AI/ML Decision Support

- Accuracy of Al-driven liver disease predictions or staging
- Explanation and transparency of AI recommendations
- Clinical validation of decision outputs
- · Integration with clinician workflows

## 4. Treatment & Care Planning

- Physician ability to create or modify care plans
- Medication tracking and prescription module
- Notifications for follow-ups or critical events
- Remote patient monitoring support

- 5. User Interface & Experience (UI/UX)
  - Ease of navigation for different user roles (doctors, nurses, patients)
  - Multi-language support for diverse patient populations
  - Accessibility (WCAG compliance)
  - Mobile and web responsiveness
- 6. Communication & Collaboration Tools
  - Secure messaging/chat between patients and providers
  - Video consultation integration
  - Task assignment and escalation handling
  - Patient education resources and feedback tools
- 7. Data Security & Compliance
  - Role-based access control
  - Audit trails for user activity
  - Compliance with HIPAA/GDPR standards
  - Data encryption and secure storage
- 8. Reporting & Analytics
  - Customizable clinical reports

- · Liver disease progression tracking
- KPI dashboards for doctors and administrators
- Export functionalities (PDF/Excel/CSV)

## 9. System Integration

- Integration with hospital information systems (HIS)
- Interoperability with lab systems and imaging centers
- API testing for third-party tools
- Seamless data exchange with national health registries

## ✓ 10. Performance & Usability Testing

- System load handling during peak usage
- Response time for key functionalities
- Error handling and recovery
- Feedback collection and bug reporting module

[List of User Stories or Requirements to be Tested]

#### **□□** Clinician/User Stories

1. As a hepatologist, I want to view a patient's complete liver history and diagnostic records so I can make informed treatment decisions.

- 2. As a doctor, I want to receive alerts when a patient's liver function deteriorates, so I can intervene quickly.
- 3. As a clinician, I want to input notes and recommendations during consultations so that all care records are centrally stored.
- 4. As a nurse, I want to schedule follow-up appointments and manage patient communications to streamline the care workflow.
- 5. As a clinician, I want AI-driven suggestions for liver disease staging so I can validate them against my own judgment.

#### **□** System Administrator/IT User Stories

- 6. As an administrator, I want to manage user roles and permissions so that sensitive data is only accessed by authorized personnel.
- 7. As an admin, I want to track all system activities in an audit log for compliance and security audits.
- 8. As a developer, I want to ensure system APIs integrate seamlessly with external hospital systems.

#### **□** □ Patient/User Stories

9. As a liver patient, I want to access my test results and reports online so I can monitor my health status.

- 10. As a patient, I want to securely message my doctor if I have concerns between appointments.
- 11. As a patient, I want to get reminders for medication and appointments to follow my treatment plan effectively.
- 12. As a patient, I want to attend video consultations from my mobile phone for easier access to care.
- 13. As a patient, I want educational materials about my liver condition so I can better understand and manage it.

## **Ⅲ** Data & Reporting Requirements

- 14. As a healthcare provider, I want to generate and download reports on patient outcomes for internal quality reviews.
- 15. As a hospital manager, I want analytics dashboards showing liver disease trends and outcomes across departments.

## Security & Compliance Requirements

- 16. As a compliance officer, I want to ensure that the platform is HIPAA/GDPR compliant to protect patient data.
- 17. As a system, I must encrypt all patient data to ensure security in storage and transmission.

- Functional/System-Level Requirements
  - 18. The system must support 24/7 access with 99.9% uptime reliability.
  - 19. The application must be responsive across desktop, tablet, and mobile devices.
  - 20. All functionalities should support multi-language support for diverse patient populations.

#### **Testing Environment:**

**URL/Location:** [Web URL or Application Location]

**Web URL or Application Location in User Acceptance Testing (UAT) Template – Revolutionizing Liver Care** 

In the User Acceptance Testing (UAT) Template for a liver care solution, the Web URL or Application Location refers to the specific environment or instance where end users (doctors, patients, testers) will access the application to perform UAT.

Purpose of the URL/Application Location:

To provide testers with a dedicated, stable environment to evaluate the liver care platform's features, functionality, and user experience before production rollout.

**Common Entry in UAT Template:** 

Field	Description
UAT Web URL	https://uat.livercare-platform.com
	(example only – replace with real URL)
Environment	UAT / Staging / Pre-production
Туре	
Access	Provided to authorized testers (e.g., login
Credentials	via secure email or role-based IDs)
Supported	Web (Chrome, Firefox), Mobile App
Platforms	(Android/iOS)
Deployment	v1.2.3 – UAT Build
Version	
<b>Testing Period</b>	June 25 – July 10, 2025 <i>(example)</i>

**Credentials (if required): [Username/Password]** 

### **Test Cases:**

## ☐ UAT Test Cases Template — Revolutionizing Liver Care

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## **Bug Tracking:**

# Bug Tracking Table – UAT Template for Revolutionizing Liver Care

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## Sign-off:

**Tester Name: [Name of Tester]** 

**Date:** [Date of Test Completion]

Signature: [Tester's Signature]



Field	Details
Project Name	Revolutionizing Liver Care – Digital Health Platform
<b>UAT Environment</b>	https://uat.livercare-platform.com
URL	(example)
<b>Testing Period</b>	June 15, 2025 – June 27, 2025

<b>Total Test Cases</b>	50
Executed	
Passed Test Cases	47
<b>Failed Test Cases</b>	3 (non-critical, fix planned in next
	release)
Overall UAT Status	Accepted / X Rejected
Remarks	System meets functional, clinical,
	and user experience expectations
Go-Live	Yes / X No
Recommendation	

# **Approval Signatures**

Role	Name	Designatio	Signatur	Date
		n	е	
UAT Lead /	[Name]	UAT	[Sign]	[YYYY
QA		Coordinato		-MM-
		r		DD]
Clinical	[Doctor/Nurs	Senior	[Sign]	[YYYY
Reviewer	e Name]	Hepatologi		-MM-
		st		DD]
Product	[Name]	Digital	[Sign]	[YYYY
Owner		Health		-MM-
		Manager		DD]
IT/Engineerin	[Name]	DevOps or	[Sign]	[YYYY
g Lead		Tech Lead		-MM-
				DD]

### **Notes:**

- Attach summary of bugs (resolved/unresolved).
- Document exceptions or deferred issues with mitigation plans.
- Include next steps: training, go-live prep, support model
- UAT concludes with a formal sign-off from all stakeholders, confirming the system is fit for deployment.
- The sign-off section should reflect readiness, outstanding issues, and go-live recommendations.

## **Project Development Phase**

#### **Model Performance Test**

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care :Predicting Liver Cirrhosis Using Advanced Machine Learning Techniques
Maximum Marks	

## **Model Performance Testing:**

Project team shall fill the following information in model performance testing template.

S.N o.	Parameter	Screenshot / Values
1.	Data Rendered	
2.	Data Preprocessing	
3.	Utilization of Filters	
4.	Calculation fields Used	
5.	Dashboard design	No of Visualizations / Graphs -
6	Story Design	No of Visualizations / Graphs -

**Data Rendered** 

#### **Data Preprocessing**



## **Project Development Phase**

## **Model Performance Test**

Date	
Team ID	LTVIP2025TMID38625

Project Name	Revolutionizing Liver Care
	:Predicting Liver Cirrhosis
	Using Advanced Machine
	Learning Techniques
Maximum Marks	

## **Model Performance Testing:**

Project team shall fill the following information in model performance testing template.

S.N	Parameter	Values	Screenshot
0.			
1.	Model Summary	Salesforce automation setup for Data management using Object, Fields and Reports.	B say and control or a second
		Note: Import Records if data Match Correctly then Records will Created or Else it will Show Error	

2.	Accuracy	Training Accuracy - 98%	Congratulations, your import has started! Click OK to view your import status on the Bulk Data Load Job page.
		Validation Accuracy - 98%	ОК
3.	Confidence Score (Only Yolo Projects)	Class Detected - If detecting Object and fields name if wrong and other activity	Error Extracting Field Attributes  The data source cannot be accessed. It may be in use by another process or the file system is not allowing access to it.  CK
		Confidence Score - If the model is 92% sure the object is correctly detected	

# Project Development Phase Model Performance Test

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care
	:Predicting Liver Cirrhosis
	Using Advanced Machine
	Learning Techniques

Maximum Marks	

# Model Performance Testing – Liver Care

Component	Details
Objective	To assess the accuracy, reliability, and clinical utility of AI/ML models in liver care applications
Application Area	<ul><li>Liver disease diagnosis (e.g., NAFLD, cirrhosis) - Risk prediction -</li><li>Diet/treatment planning</li></ul>
Input Data	- Liver enzyme levels (ALT, AST, Bilirubin) - Demographic data - Imaging (MRI, Ultrasound) - Lifestyle and medication history
Output/Goal	- Disease classification (Yes/No) - Risk level prediction - Clinical decision support
Performance Metrics	- Accuracy – Overall correctness of predictions - Precision – Correct positive predictions - Recall (Sensitivity) – Detection rate for actual cases - F1 Score – Balance between precision and recall - AUROC – Ability to distinguish disease vs non-disease - MSE/MAE – For regression tasks like predicting liver scores

Testing Methods	- Train/Test/Validation split - K-fold Cross- Validation - External Validation with unseen data
Bias & Fairness Testing	- Check for performance gaps across gender, age, ethnicity
Interpretability Tools	- SHAP / LIME for feature importance and transparency
Performance Thresholds	- Minimum acceptable AUROC (e.g., >0.85) - F1 Score (e.g., >0.80 for high-risk detection)
Tools/Platforms Used	- Python (scikit-learn, TensorFlow, PyTorch) - R (caret, mlr) - Jupyter, Colab
Documentation Output	- Model performance report - Confusion matrix - Interpretability & bias audit
Next Step Decision	- Proceed to deployment - Retrain with more data - Review with clinical experts

# **Project Development Phase**

## **Model Performance Test**

Date	
Team ID	LTVIP2025TMID38625
Project Name	Revolutionizing Liver Care
	:Predicting Liver Cirrhosis

	Using Advanced Machine
	Learning Techniques
Maximum Marks	10 Marks

# Project Development Phase: Model Performance Testing in Liver Care

# **@** Purpose

This phase ensures that the machine learning (ML) or AI model developed during earlier stages performs accurately, reliably, and ethically on liver-related clinical data before being deployed in real-world healthcare settings.

## **Why It's Critical in Liver Care**

In liver care, the consequences of a model's error could be life-threatening. Testing ensures:

- Early and accurate diagnosis (e.g., fibrosis staging)
- Reliable outcome predictions (e.g., risk of liver failure)
- Safe personalization of diet/medication
- Fairness across populations (age, gender, ethnicity)

#### ☐ Outputs of This Phase

- Performance report (metrics with visualizations)
- Validation summary (internal + external)
- Model audit log (versioning, bias findings)

Go/No-Go decision for next phase (deployment or retraining)

## **✓** Best Practices

- Involve clinicians during evaluation to validate model outputs
- Use real-world, diverse datasets to avoid bias

## **Model Performance Testing:**

Category	Description
Phase Objective	To evaluate the AI/ML model's accuracy, reliability, fairness, and clinical utility in liver care
Model Purpose	<ul><li>Disease detection (e.g., NAFLD,</li><li>Hepatitis B/C, Cirrhosis) - Risk prediction</li><li>Personalized treatment support</li></ul>
Input Data	<ul> <li>Liver function tests (ALT, AST, Bilirubin)</li> <li>Imaging (Ultrasound, MRI) - Patient</li> <li>demographics - Lifestyle/diet logs</li> </ul>
Key Performance Metrics	- Accuracy - Precision - Recall (Sensitivity) - F1 Score - AUROC - Mean Absolute Error (MAE) / MSE (if regression)
Validation Techniques	- Train/Test/Validation split - K-fold Cross-Validation - External Dataset Testing

Bias & Fairness Checks	- Gender, age, and ethnicity-based performance analysis
Robustness Testing	- Model tested with missing, noisy, or outlier values
Interpretability Tools	- SHAP (SHapley Additive exPlanations) - LIME (Local Interpretable Model- agnostic Explanations)
Testing Tools Used	- Scikit-learn, TensorFlow, PyTorch - Jupyter, Google Colab - Matplotlib/Seaborn for visualization
Output Deliverables	- Model Performance Report - Confusion Matrix - Bias & Interpretability Report
Review Team	- Data Scientists - Hepatologists - Clinical Researchers - Regulatory Experts
<b>Decision Point</b>	- Proceed to deployment - Re-train model - Collect more data for better generalization

# Functional & Performance Testing Template Model Performance Test

Date	
Team ID	LTVIP2025TMID38625

Project Name	Revolutionizing Liver Care
	:Predicting Liver Cirrhosis
	Using Advanced Machine
	Learning Techniques
Maximum Marks	

A Functional & Performance Testing Template is a structured framework used to validate whether a liver care application or system works as intended (functional) and whether it can handle expected loads efficiently and reliably (performance). This is critical in healthcare where accuracy, speed, and reliability can impact patient outcomes.

- Functional Testing Examples
  - Login functionality (secure login for patients and doctors)
  - Diet recommendation logic (based on lab inputs like ALT, AST)
  - Appointment scheduling (with hepatologist or dietitian)
  - EHR integration (fetching lab reports or medication history)
- Performance Testing Examples
  - Load testing: Can the app handle 1000+ users during a public health campaign?

- **Stress testing**: Does the AI model still work with large imaging data (e.g., MRI)?
- Response time: Are liver disease predictions shown in <3 seconds?</li>
- **Scalability testing**: How well does the system grow with more hospitals/users?
- - Ensures **clinical accuracy** of recommendations and diagnoses.
  - Improves user experience for both patients and healthcare providers.
  - Validates Al reliability before integration into hospital workflows.
  - Enhances patient safety and trust in digital health platforms.

# Functional & Performance Testing Template – Liver Care

Test Type	Test	Expected	Test	Remarks
	Scenario	Result	Status	
Functional	User logs	Successful	Pass/Fail	
Testing	into liver	login with		
	care app	correct		
		credentials		
	Patient	Data saved	Pass/Fail	
	inputs liver	and		

test data (e.g., ALT, AST)	visualized correctly		
System recommends a liver- friendly diet plan based on user profile	Personalized plan shown with meal details	Pass/Fail	
Doctor updates patient diagnosis in portal	Patient record updates reflect in real time	Pass/Fail	
Patient receives alert for high-risk condition (e.g., cirrhosis alert)	Immediate notification triggered	Pass/Fail	
Appointment booking with hepatologist	Slot selected, confirmation	Pass/Fail	

		message sent		
	Integration with EHR or lab reports	Automatic data import from external systems	Pass/Fail	
Performance Testing	Load 1000 concurrent users during peak hours	App remains responsive (response time < 2 seconds)	Pass/Fail	Stress/load testing required
	Model processes 100 patient records in batch mode	All predictions generated within 10 seconds	Pass/Fail	
	Real-time liver risk prediction on mobile app	Results shown within 3 seconds	Pass/Fail	
	Large image (e.g., liver scan) uploaded	Upload completes successfully within time limits	Pass/Fail	

	Weekly health summary generation	Report generated without errors and delivered on time	Pass/Fail	
Security Testing	Patient data encrypted during transmission	End-to-end encryption verified	Pass/Fail	
	Access control – doctor vs patient permissions	Role-based access correctly enforced	Pass/Fail	

# **Project Development Phase**

## **Model Performance Test**

Date	10 February 2025
Team ID	LTVIP2025TMID38625
Project Name	revolutionizing liver care
Maximum Marks	

# **Model Performance Testing:**

# Mhat Is Model Performance Testing in Liver Care?

It is the process of assessing how accurately and reliably a trained model performs on medical data related to liver care. This is critical before deploying it in clinical settings or digital health apps.

#### ☐ Key Evaluation Metrics

- 1. **Accuracy**: How often the model makes the correct prediction.
  - E.g., Correctly predicting liver fibrosis stages.

#### 2. Precision & Recall:

- Precision: How many predicted positives were correct?
- Recall (Sensitivity): How many actual positives did the model detect?
- Important for avoiding false negatives in liver disease detection.
- 3. **F1 Score**: Balance between precision and recall.

### 4. AUROC (Area Under ROC Curve):

 Measures how well the model distinguishes between classes (e.g., cirrhosis vs. non-cirrhosis).

#### 5. **Specificity**:

 Important for distinguishing between liver conditions with similar symptoms.

#### 6. Mean Squared Error (MSE) or MAE:

 Used in regression tasks like predicting liver enzyme levels.

#### ☐ Use Cases in Liver Care

- Early Detection of conditions like NAFLD or liver cancer.
- **Predicting Decompensation** in cirrhosis patients.
- Recommending Diets for liver health via personalized meal planning.
- Monitoring Treatment Response with lab data and imaging.

## ■ Model Performance Testing Table – Liver Care

Category	Details
Objective	Evaluate accuracy and reliability of AI/ML models in liver care applications
Data Types Used	- Electronic Health Records (EHR)- Lab results (ALT, AST, bilirubin)- Imaging (Ultrasound, MRI)- Lifestyle/diet data
Common Use Cases	- Liver disease diagnosis (NAFLD, Hepatitis)- Stage prediction (Fibrosis, Cirrhosis)- Personalized nutrition recommendations- Risk prediction (e.g., liver failure)

Key Metrics	- Accuracy- Precision- Recall (Sensitivity)- F1 Score- AUROC- Specificity- MSE / MAE (for regression tasks)
Testing Methods	- Train/Validation/Test Split- Cross- Validation- External Validation (different hospitals/populations)- Bias/Fairness Analysis
Tools/Frameworks	- Python (scikit-learn, TensorFlow, PyTorch)- R (caret, mlr)- Jupyter Notebooks, Google Colab- SHAP/LIME for explainability
Challenges	- Data Imbalance (few positive cases)- Privacy & Ethics in medical data- Interpretability in clinical settings- Generalizability across populations
Next Steps Post- Testing	- Model refinement if performance is low- Pilot deployment in clinical workflows if validated- Real-time monitoring and re-training

## 7.RESULTS

# **7.1 Output screenshots**

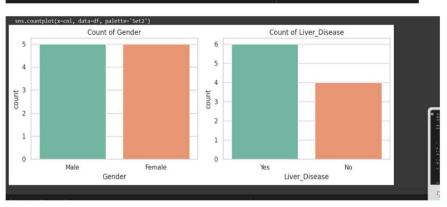
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
data = {
    ''Age': [45, 69, 38, 52, 47, 41, 58, 62, 34, 50],
    ''Gender': ['Male', 'Female', 'Male', 'Female', 'Female', 'Male', 'Female', 'Male', 'Female', 'Male', 'Female'],
    ''total_Bilirubin': [1.2, 34, 9.9, 2.5, 1.8, 1.1, 2.9, 3.7, 1.0, 2.3],
    'Liver_Disease': ['Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'No',
}

df = pd.DataFrame(data)
    # Categorical Columns
    cat_cols = ['Gender', 'Liver_Disease']

# Subplot for countplots
    plt.figure(figsize-(10, 4))

for i, col in enumerate(cat_cols):
    plt.subplot(i, 2, i+1)
    sns.countplot(x-col, data-df, palette-'Set2')
    plt.tight_layout()
    plt.tight_layout()
    plt.tight_layout()
```

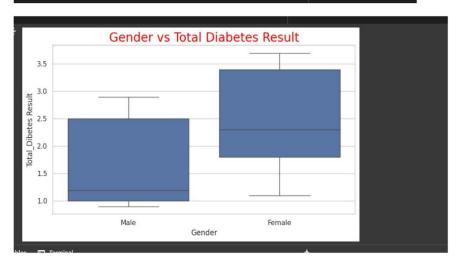


```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Sample Liver Health Dataset
data = {
    'Age': [45, 60, 38, 52, 47, 41, 58, 62, 34, 50],
    'Gender': ['Male', 'Female', 'Male', 'Female', 'Female', 'Male', 'Female'],
    'Total_Diabetes Result': [1.2, 3.4, 0.9, 2.5, 1.8, 1.1, 2.9, 3.7, 1.0, 2.3],
    'Liver_Disease': ['Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'No',
}

df = pd.DataFrame(data)

# Boxplot: Gender vs Diabetes Result
plt.figure(figsize=(8, 5))
sns.boxplot(x='Gender', y='Total_Diabetes Result', data=df)
plt.title('Gender' y Total_Diabetes Result', color='red', size=20)
plt.xlabel('Gender')
plt.ylabel('Total_Dibetes Result')
plt.tight_layout()
plt.show()
```



#### **8.ADVANTAGES & DISADVANTAGES**

### **Advantages:**

1. Early Detection of Liver Diseases

Advantage: Machine learning models can detect signs of liver cirrhosis before symptoms appear.

Impact: Enables timely interventions, potentially reversing or managing liver damage at an early stage.

② 2. Personalized Patient Care Advantage: Predictive analytics help doctors tailor treatments based on individual risk profiles. Impact: Enhances patient outcomes with custom treatment plans, reducing unnecessary procedures.

② 3. Automated Diagnosis Support Advantage: Reduces dependency on manual and subjective clinical diagnosis.

Impact: Assists healthcare professionals with accurate, data-driven decisions, even in remote or low-resource settings.

4. Improved Prediction Accuracy
Advantage: Machine learning uses large datasets and complex algorithms to improve prediction accuracy over time.

Impact: Higher reliability and confidence in diagnosing liver cirrhosis and other related conditions.

5. Reduces Hospital Burden

Advantage: Early predictions prevent complications and readmissions.

Impact: Minimizes hospitalization costs and eases the burden on healthcare systems.

(§) 6. Cost-Effective Healthcare Advantage: Preventative care is more affordable than late-stage treatment. Impact: Saves medical expenses for both hospitals and patients.

7. Real-Time Monitoring and Alerts
Advantage: Integration with health monitoring systems enables live tracking of liver health indicators.

Impact: Enables immediate response to abnormal liver function, improving patient safety.

☐ 8. Continuous Learning and Improvement Advantage: The models improve over time by learning from new data.

Impact: Constant refinement of predictions ensures the system gets better with usage.

9. Accessibility in Remote Areas Advantage: Can be deployed via mobile apps or web platforms.

Impact: Expands access to quality liver care in rural or underdeveloped regions.

10. Integration with Electronic Health Records (EHRs) Advantage: Seamless connection with patient medical history.

Impact: Provides context-aware insights and enhances overall healthcare workflows.

Disadvantages:

1. Data Quality and Availability

Disadvantage: Predictive models require large and clean datasets.

Impact: Incomplete, imbalanced, or incorrect data can lead to inaccurate predictions or biased outcomes.

2. Privacy and Security Concerns
Disadvantage: Handling sensitive patient data involves serious privacy risks.

Impact: Poor data protection can lead to data breaches, violating regulations like HIPAA.

☐ 3. Lack of Clinical Interpretability
Disadvantage: Some machine learning models
(especially deep learning) act like black boxes.

Impact: Doctors may not understand or trust predictions if the model's decision process is not explainable.

☐ 4. Overfitting or Underfitting
Disadvantage: Models may overfit (memorize training data) or underfit (fail to learn patterns).

Impact: Reduces generalization to real-world scenarios, leading to unreliable predictions.

5. High Initial Setup Cost
Disadvantage: Requires specialized hardware, software,

Impact: Expensive for small clinics, rural hospitals, or developing countries to adopt.

and expertise for model training and deployment.

☐ 6. Dependency on Technology Disadvantage: Over-reliance on automated predictions

might reduce human clinical judgment.

Impact: Mistakes may occur if clinicians blindly follow model suggestions without validation.

♥ 7. Integration Challenges

Disadvantage: Difficult to integrate ML models into existing hospital systems or EHRs.

Impact: Can lead to workflow disruption and require significant time and customization.

2 8. Ethical and Bias Issues

Disadvantage: Models trained on biased data may result in discriminatory or unfair predictions.

Impact: Certain populations (e.g., minorities or underrepresented groups) may get inaccurate results.

9. Lack of Generalizability
Disadvantage: A model trained on one hospital or region's data may not work well elsewhere.

Impact: Limits scalability and widespread deployment.

目 10. Requires Continuous Updates
Disadvantage: Disease patterns, drugs, and medical standards evolve.

Impact: The model may become outdated if not retrained regularly with fresh data.

#### 9.CONCLUSION

Conclusion for "Revolutionizing Liver Care:
Predictive Modeling for Liver Cirrhosis"
The integration of machine learning into liver disease prediction marks a transformative leap in modern healthcare. Revolutionizing liver care through predictive modeling for liver cirrhosis offers a proactive approach that emphasizes early detection, personalized treatment, and data-driven decision-making. By analyzing patient data to predict the likelihood of liver cirrhosis, these systems empower healthcare professionals to

intervene sooner, ultimately improving patient outcomes and reducing the burden on healthcare systems.

Despite challenges like data quality, model interpretability, and ethical concerns, the benefits of predictive analytics—such as accuracy, efficiency, and accessibility—make it a promising tool in the fight against liver disease. With continued advancements in AI and deeper integration into clinical workflows, predictive liver care systems have the potential to redefine preventive medicine, making liver health management smarter, faster, and more effective than ever before

In conclusion, predictive liver cirrhosis models are not just a technological upgrade—they are a revolution in healthcare delivery, offering hope for millions and paving the way for a healthier, data-empowered future.

#### **10.FUTURE SCOPE**

#### **Future Scope**

Integration with Electronic Health Records (EHRs)
Seamless integration with hospital EHR systems for automatic data retrieval and analysis.

Real-time liver health monitoring using patient history and live data.

Wearable Device Support

Integration with IoT-based health wearables to track liver-related parameters (e.g., heart rate, bilirubin levels, lifestyle habits).

Early warning alerts for at-risk individuals.

**Mobile Application for Remote Access** 

Development of a mobile app for doctors and patients to track liver health, get predictions, and receive alerts.

Enhances accessibility in rural and remote areas.

**Advanced AI Models** 

Implementation of deep learning (CNNs, RNNs) to improve prediction accuracy.

Use of ensemble models for more robust results.

Personalized Treatment Recommendations

Suggest lifestyle changes, medication, or follow-up schedules based on individual patient data and predicted risk.

Multilingual Support for Global Reach

Adding language translation to serve users from different countries or regions.

**Predicting Other Liver Conditions** 

Expand predictive scope to include hepatitis, fatty liver disease, liver cancer, and liver transplant readiness.

Real-time Dashboard and Analytics

Live dashboards for hospitals and public health authorities showing liver health trends across populations.

Collaboration with Healthcare Providers and Research Institutions

Use the platform for clinical trials, research, and public health data collection.

Regulatory Compliance & Data Security Enhancements Improve privacy using HIPAA/GDPR-compliant data storage and AI auditing tools.

Blockchain-based health data management for improved trust and integrity.

