LIVERGUARD

AI-Driven IoT System for Early Liver Disease Detection and Monitoring

Mentors:

Dr. Rohit Ahuja (CSED Department)

Dr. Paluck Arora(CSED Department)

Team Members:

Aishwary Srivastava
Nitin Kumar Rajvanshi
Simrat Kaur
Mustansir Kanor
Sneha Upadhyay
Vaishnavi Agrawal
Abheet Singh
Chirag Bagga
Lovleen Shukla
Rishabh Suri

PROJECT OVERVIEW

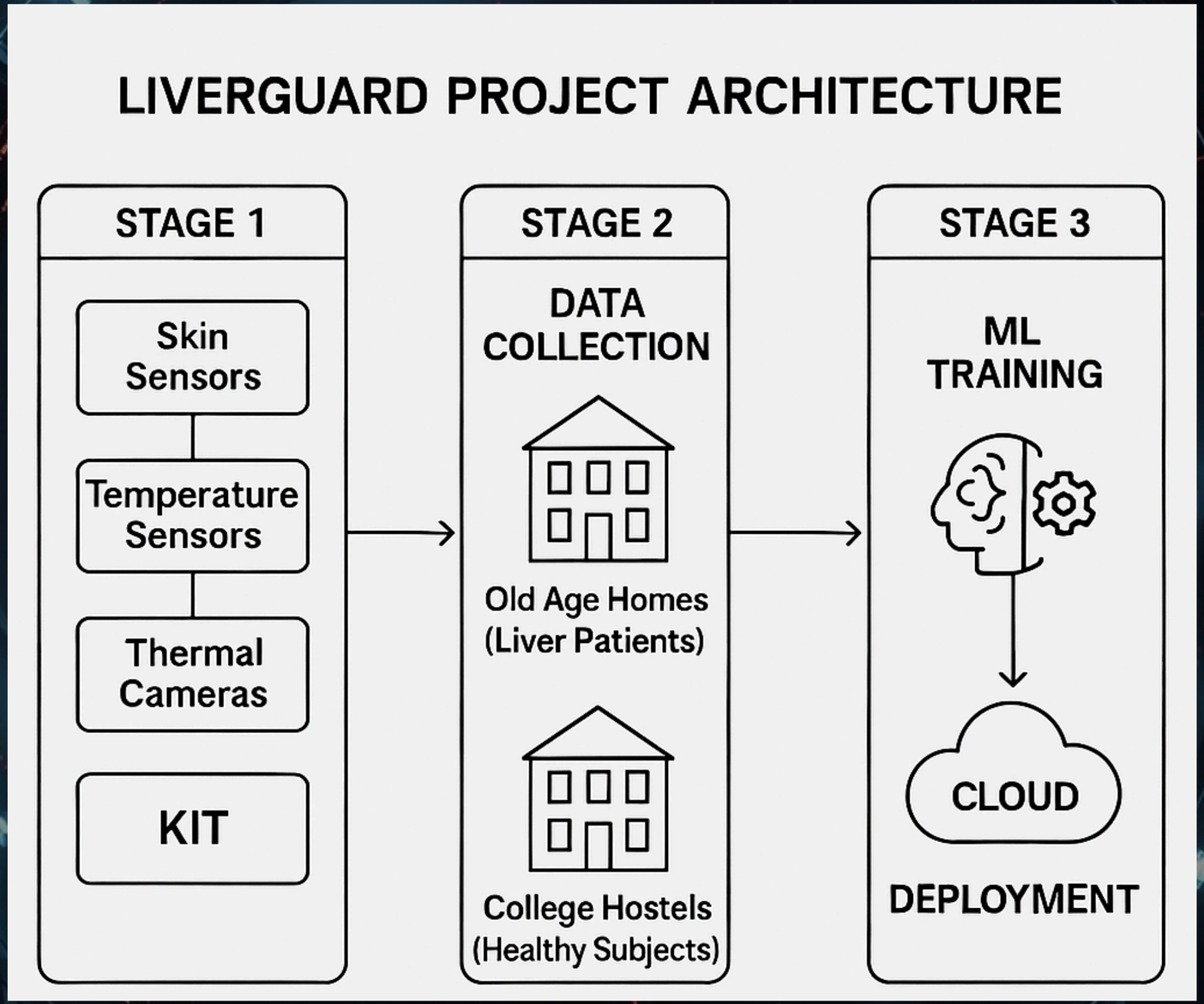
Key components include:

- TEMPERATURE SENSORS
- THERMAL CAMERA
- SKIN SENSORS

The project leverages Artificial Intelligence (AI) and the Internet of Things (IoT) to:

- Enable continuous remote monitoring
- Improve diagnostic accuracy
- Support early medical intervention

ARCHITECTURE

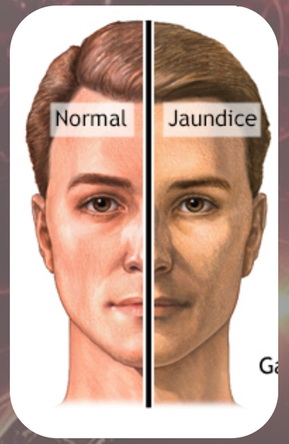


PARAMETERS

Skin impedance:

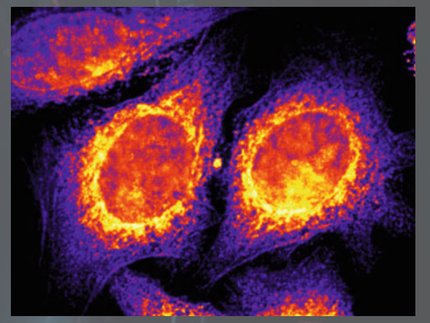
Skin impedance measured by a soft, adhesive on-skin sensor offers a non-invasive way to distinguish between healthy and fatty liver tissues by detecting changes in electrical properties related to fat infiltration.

Skin Colour:



Skin colour measurement provides a rapid, non-invasive method for detecting changes associated with liver disease, especially jaundice and hyperpigmentation.

Thermal Imaging:



Thermal imaging provides a non-contact approach to detect abnormal temperature patterns on the skin surface, which can signal inflammation or altered blood flow caused by underlying liver dysfunction.

LITERATURE REVIEW

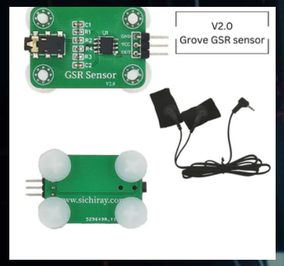
Parameter	Paper Link	Outcomes
SKIN IMPEDANCE	https://www.ccjm.org/content/88/4/210	In this paper the patient was suffering from puffy hands leading to fluid retention which was linked to liver cirrohsis
	https://pmc.ncbi.nlm.nih.gov/articles/PMC9257870/	This paper shows change in electrolyte levels of patients with different liver diseases
SKIN COLOUR	https://www.mdpi.com/2673-4532/6/1/6	This paper shows links of skin colour with jaundice in new borns
	https://www.dermatologypaper.com/article/view/83/4-2-5	In this reasearch they used the same sensor which is used in our prototype for jaundice detection
THERMAL IMAGING	https://pmc.ncbi.nlm.nih.gov/articles/PMC7511937/#Sec7	Shows links of thermal image with NAFLD
	https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5244427	Blue light emission trends with bilurubin

HARDWARE USED

Important Sensors

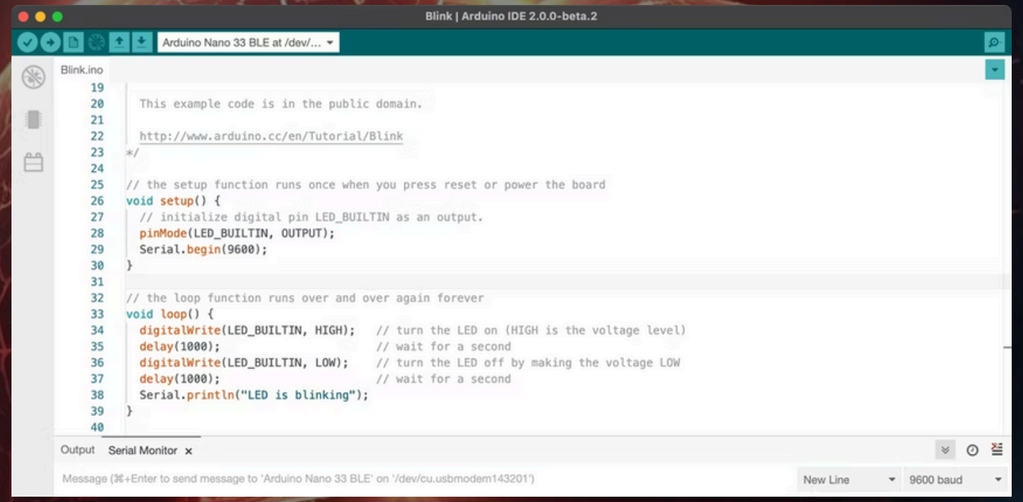
Color Sensor
RGB Module

IR Array Thermal
Imaging Camera



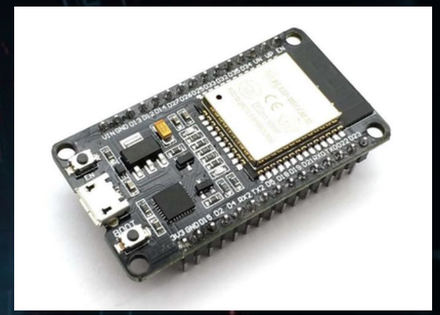
Galvanic Skin
Response Module
Current Sensor Kit

IDE AND MICROCONTROLLER USED



Arduino IDE:

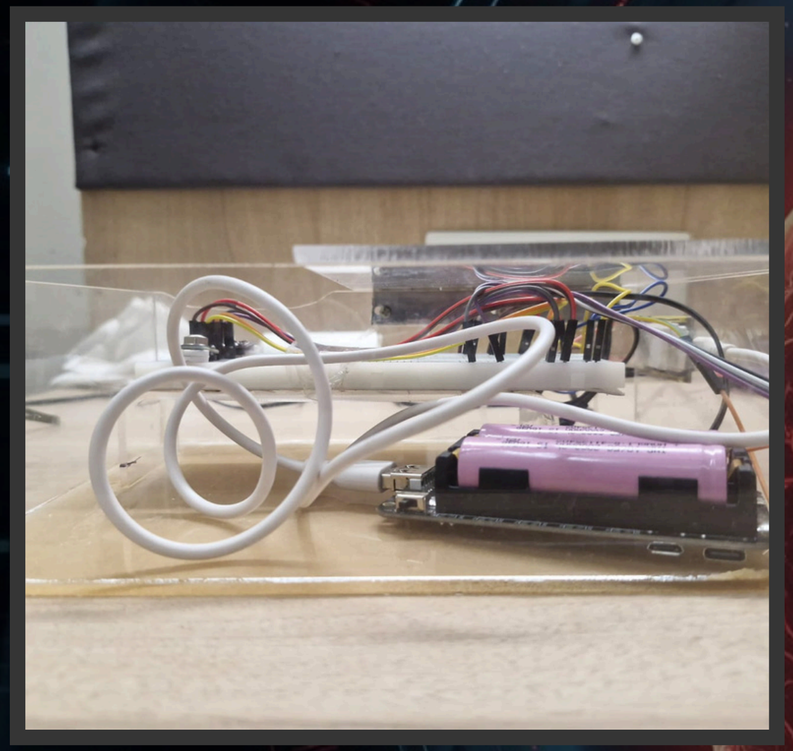
- Easy platform for coding and uploading to microcontrollers
- Supports many sensors and libraries
- Widely used and beginner-friendly

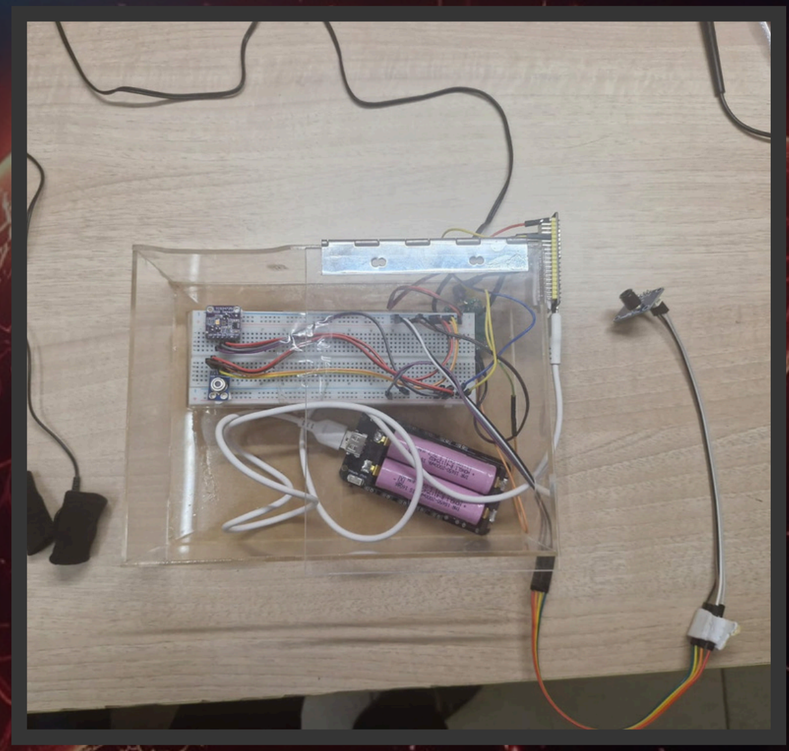


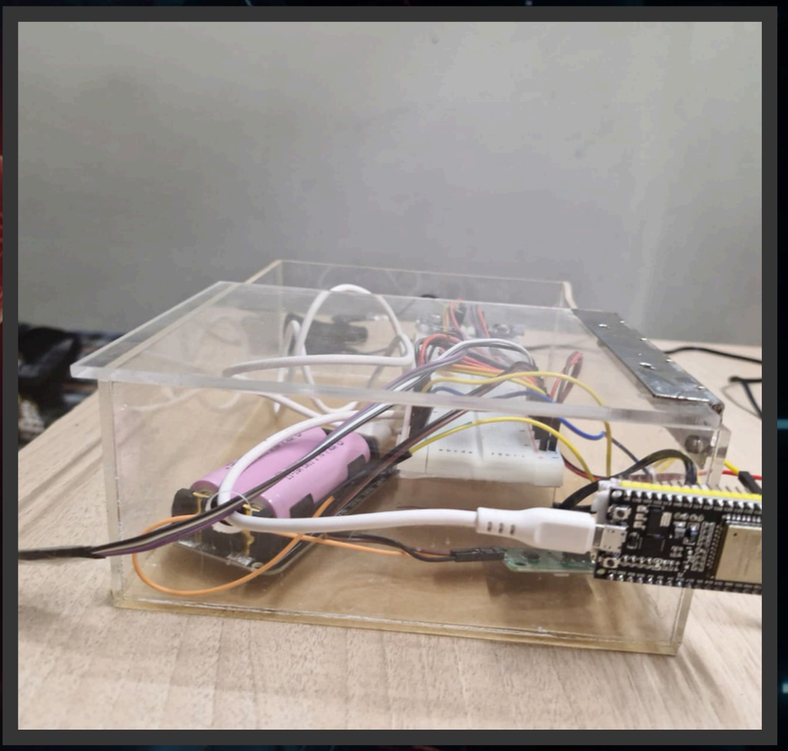
ESP32

- Powerful microcontroller with WiFi/Bluetooth
- Connects to multiple sensor

HARDWARE





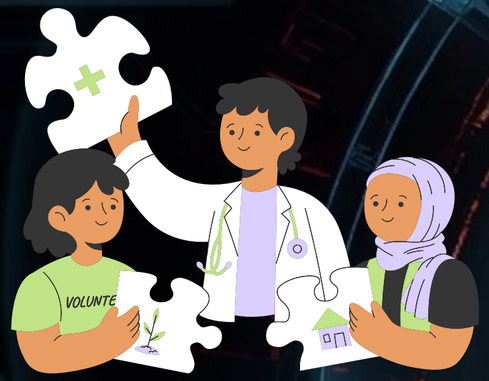


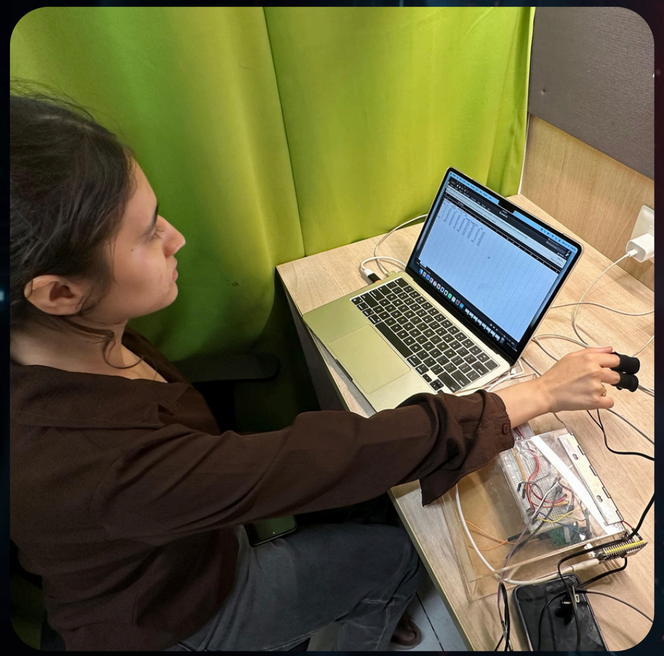
The final product has been fabricated using acrylic sheets and laser cutting technology, and includes a movable closing flap that helps maintain uninterrupted connections.

DATASET COLLECTION

1) Old- Age Home :

2. College Students :





INTERFACE

SENSOR INPUT PAGE

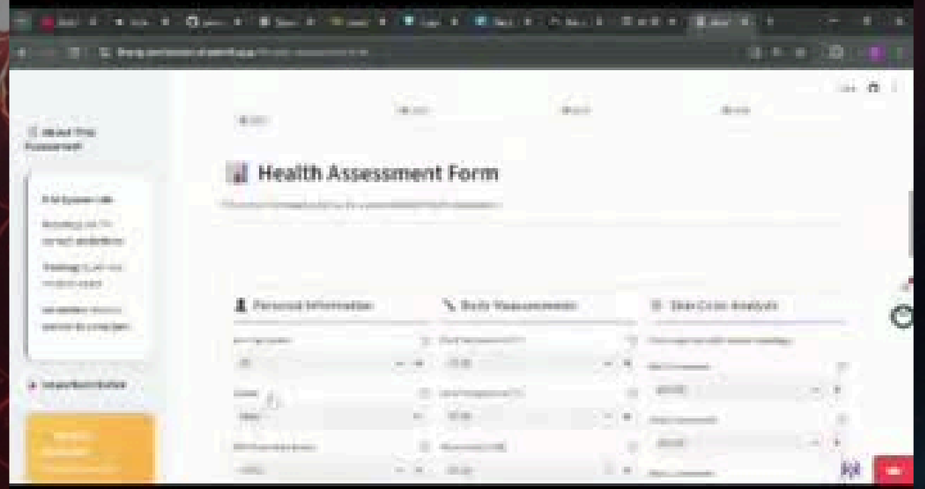
CSV FILE GENERATED

Liver Heal	Age	Gender	Weight (kg	Height (cm)				
Yes	20	Male	60	172				
Sample	R	G	B	C	Temp90614	Temp90640	GSR	BMI
1	468	327	222	1012	29.93	35.74	762	20.28
2	385	273	185	839	30.05	35.79	769	20.28
3	377	259	174	805	30.05	35.64	765	20.28
4	353	239	161	748	30.03	35.63	755	20.28
5	436	286	191	906	30.31	35.44	775	20.28
6	409	269	179	851	30.19	35.33	770	20.28
7	402	265	177	839	30.15	35.48	763	20.28
Average	404.29	274	184.14	857.14	30.1	35.58	765.57	20.28

REAL- TIME APP DEPLOYMENT

LIVERGUARD AI

Deployed Website 💻



1) Input Patient data

2) Get detailed health report

ML ARCHITECTURE

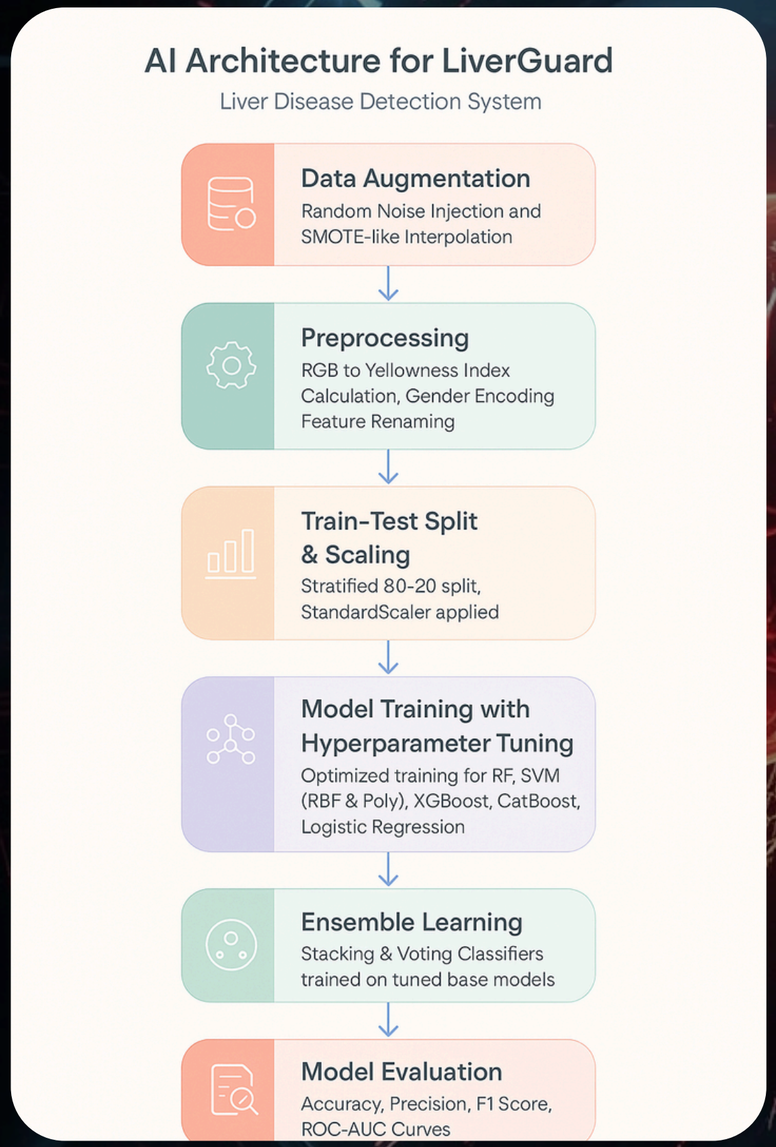
1. Data Augmentation :
Random noise injection and SMOTE interpolation

2. Data preprocessing :
Skin **y**ellowness index calculation using RGB values and encoding categorical variables

3. Model Training :
Training base layer models (RF, SVM, LR, XGB and CatB) with hyperparameter tuning

4. Ensemble Learning :
Stacking and soft voting on trained models

ML ARCHITECTURE



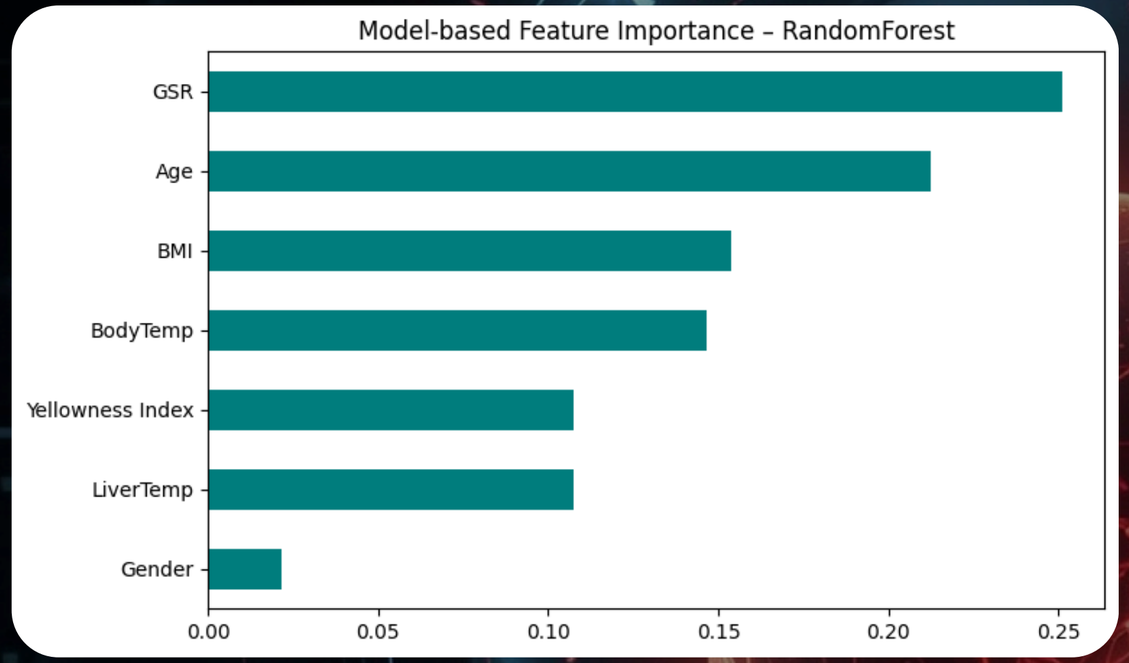
5. Model evaluation :
Calculating Accuracy, Precision, F1, ROC-AUC

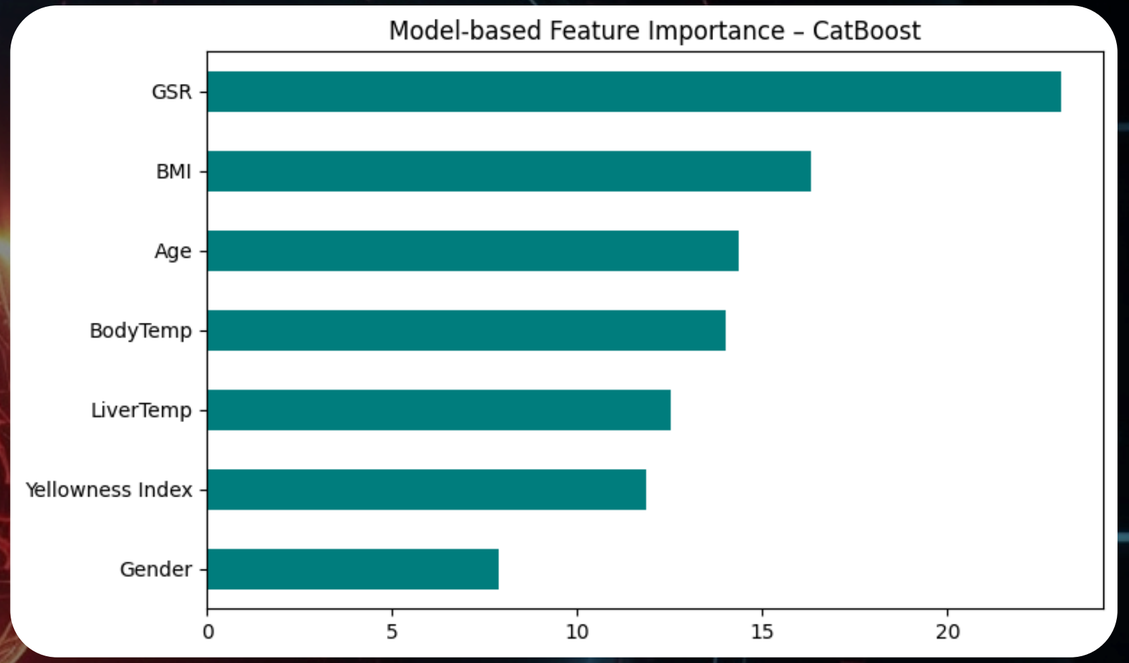
6. Explainability :
Feature importance graphs

7. On-time inference :
User input → Preprocess → Predict :
Healthy / Unhealthy

8. Model dumping :
Exporting stacking and soft voting models as pickle files

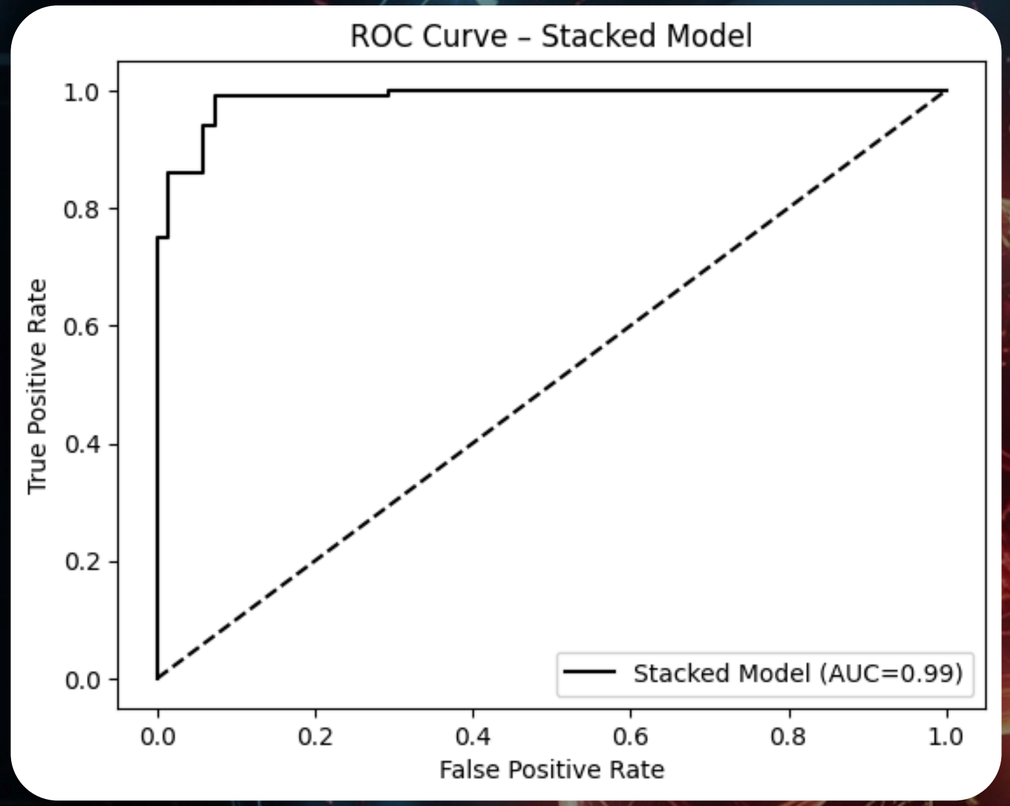
FEATURE IMPORTANCE



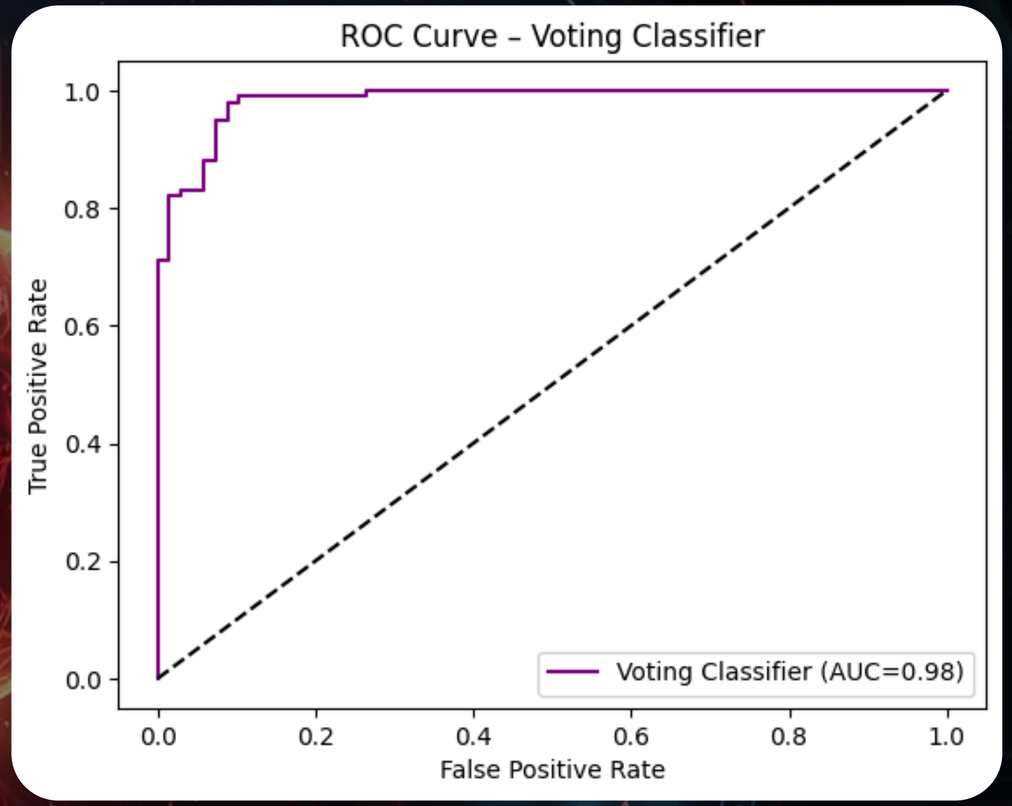


1. GSR value is the top predictor of liver health.
2. Age, BMI, and Body Temperature are strong secondary indicators.
3. Gender affects liver health the least.

RESULTS



Accuracy : 95%
ROC-AUC Score : 0.987
F1 Score : 0.93 (Unhealthy) and 0.96 (Healthy)
Precision : 0.94 (Unhealthy) and 0.95 (Healthy)



Accuracy : 95%
ROC-AUC Score : 0.983
F1 Score : 0.94 (Unhealthy) and 0.96 (Healthy)
Precision : 0.98 (Unhealthy) and 0.93 (Healthy)

REFERENCES

[1]Li, N., Jiang, Y., Gong, G., Han, G. and Ma, J., 2018. Non-invasive assessment model of liver disease severity by serum markers using cloud computing and internet of things. IEEE Access, 6, pp.33969-33976.

[2]Swain, S., Mohanty, M.N. and Pattanayak, B.K., 2024, November. Precision medicine in hepatology: harnessing IoT and machine learning for personalized liver disease stage prediction. In Int J Reconfigurable & Embedded Syst ISSN (Vol. 2089, No. 4864, p. 4864).

[3]Guo, J., Bu, R., Shen, W. and Feng, T., 2025. Towards robust multimodal ultrasound classification for liver tumor diagnosis: A generative approach to modality missingness. Computer Methods and Programs in Biomedicine, 265, p.108759.

[4]Li, T., Guo, J., Tao, W., Bu, R. and Feng, T., 2025. MUCM-FLLs: Multimodal ultrasound-based classification model for focal liver lesions. Biomedical Signal Processing and Control, 107, p.107864.


THANK
YOU