RESEARCH PAPER

Design and Implementation of a Machine Learning-Based Smart Liver Diagnostic System with Integrated Sensor and USB Communication Interface

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ABSTRACT: Liver diseases are among the leading health concerns worldwide, yet their diagnosis still largely depends on invasive blood tests that measure biomarkers such as alanine aminotransferase (ALT), aspartate aminotransferase (AST), and bilirubin. While effective, these methods are not suitable for frequent monitoring and often delay early detection. In this work, a smart and non-invasive liver diagnostic system is proposed, combining multi-sensor hardware with machine learning to enable continuous and real-time health assessment. The system is built around an ESP32 microcontroller and integrates sensors to capture both physiological and biochemical signals. The collected data is transmitted to a host system, where it undergoes preprocessing and feature extraction before being analyzed using an XGBoost model for predicting liver health status. To improve transparency, SHAP-based explanations are used to interpret model predictions. The system is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score. Overall, the proposed approach offers a practical, cost-effective, and scalable solution for non-invasive liver monitoring, with strong potential to support early detection and remote healthcare applications.

Keywords--*Smart Liver Diagnostics. Smart Liver Diagnostic System; Non-Invasive Monitoring; Biomedical IoT; Machine Learning; XGBoost; SHAP Explainability; Liver Biomarkers (ALT, AST, Bilirubin); Real-Time Health Monitoring*

I. Introduction

Liver disease is one of the biggest worldwide health problems, and there are many death due to liver disease every year. The development of chronic liver disease (for example: NAFLD, hepatitis, cirrhosis) is often long and goes unnoticed until they present with symptoms. Therefore, a timely diagnosis is crucial to avoid complications before they are evident [1]. Currently, liver function tests are performed by using blood tests for biochemical markers of liver function such as ALT, AST and bilirubin [2]. These biochemical markers provide information that can be relied on for clinical purposes; however, the process of obtaining the sample is invasive, requires someone with special training and is not appropriate for use as an ongoing or real-time monitoring tool. Repeated blood sampling may lead to decreased patient comfort and limited access to follow-up appointment, particularly when an individual lives in a remote healthcare area.

A new opportunity to provide non-invasive monitoring of physiological and biochemical parameters has recently become available through the use of wearable biosensors. Sweat is an ideal biofluid to use as a biomarker for sweat because it consists of several metabolites, electrolytes, and other analytes that represent the metabolic state of the body [3]. Furthermore, research has validated that wearable sweat sensors can detect biomarkers associated with metabolic and inflammatory conditions with a measurable correlation to blood-based measurements [4]. These findings suggest that sweat based monitoring could provide valuable information for assessing liver health when used in conjunction with appropriate analytical models. Artificial Intelligence (AI) and Machine Learning (ML) methods are now commonly applied in healthcare for diagnostic purposes through the analysis of complex bioscience metrics. One of the most powerful ML algorithms for this purpose is Extreme Gradient Boosting (XGBoost), which has emerged to be one of the bestperforming ML algorithms for classification and prediction tasks due to its ability to run very quickly and with accuracy [5]. However, understanding how algorithms generate their output is critically important within the medical domain. The use of Shapley Additive Explanations (SHAP) provides a systematic approach to explaining the output of the prediction algorithm by quantifying the contribution of each input feature to the final output, thus creating greater transparency and increased trust in clinical application [6]. This project is to develop an integrated Smart Liver Diagnostic System that combines the use of Embedded Multi-Sensor Hardware and Explainable Artificial Intelligence Software Analytics. The hardware platform consists of an ESP32 Microcontroller and the following components: MAX30102 Sensor (for physiological continuous

monitoring), Colour Sensor (to detect colour changes for chemical reactions), Load Cell (for measuring the mass of the sample), and Ultrasonic Sensor (to monitor liquid level). The Smart Liver Diagnostic System will utilize perspiration as the medium through which analyses can be performed in order to identify multiple metabolites associated with liver enzymatic action (for example, ammonia, uric acid, glucose, lactate, cortisol, Electrolytes (Na^+, K^+, Cl^-) heavy metals, skin temperature, and pH). The analysis framework developed using Python employs the XGBoost algorithm to create predictions based on input data. The SHAP methodology is also utilized in order to analyze the logic behind the predictions and provide a correct interpretation of the results. By using these frameworks, we create a compact, non-invasive and real-time solution for monitoring liver function which provides early detection, continual assessment of liver health status, and can serve as an ongoing source of information for the care of patients who are located in remote areas.

II. LITERATURE SURVEY

The literature shows that while both sensor technology and analytical methods have developed independently, there are limited integrated systems which utilized non-invasive multiparameter sensing and predictive machine learning to provide liver disease diagnoses. Based on the current literature gap, there is a need for research such as this explanation of the development of an integrated system for monitoring liver health. Liver diseases represent a significant global health concern, as highlighted by the World Health Organization, which reports a rising incidence of liver-related disorders worldwide [1]. Traditionally, liver function assessment relies on biochemical markers such as alanine aminotransferase (ALT), aspartate aminotransferase (AST), and bilirubin, which are clinically validated indicators for diagnosing liver conditions [2]. However, these methods are invasive and not suitable for continuous monitoring, motivating the need for non-invasive alternatives.Recent advancements in wearable biosensors have enabled non-invasive monitoring of physiological and biochemical parameters. Kim et al. demonstrated that sweat-based biomarkers can provide valuable insights into metabolic conditions, establishing a correlation between sweat analytes and blood-based measurements [3]. Similarly, Davis et al. developed a sweat-based biosensor system capable of monitoring inflammatory markers in liver disease patients, confirming the feasibility of sweat as an alternative biofluid for disease monitoring [4].

The integration of machine learning has further enhanced the capability of biosensor-based systems. Chen and Guestrin introduced XGBoost, a powerful ensemble learning algorithm capable of handling complex datasets with improved predictive accuracy [5]. To address the need for interpretability in medical applications, Lundberg and Lee proposed SHAP, which explains model predictions by quantifying the contribution of each input feature [6].Advancements in sensor technology have also focused on improving multi-parameter detection. Zhou et al. developed a flexible multi-analyte sweat sensor patch capable of simultaneously detecting electrolytes and metabolites, emphasizing the importance of sensor integration and signal stability [7]. Yang et al. proposed a wearable electrochemical sensor array for continuous monitoring of lactate and glucose, although challenges such as signal interference and calibration were noted [8].Machine learning applications in biomedical signal analysis have been further explored by Lee et al., who demonstrated improved classification of metabolic conditions using physiological signals [9]. In addition, explainable AI techniques have been increasingly adopted in healthcare, with studies highlighting the importance of interpretable models in clinical decision-making [10].Further research by Patel et al. introduced a microfluidic sweat sensor for detecting ammonia and lactate, providing insights into metabolic health; however, the study did not establish a direct relationship with liver-specific biomarkers [11]. Chen et al. reviewed wearable systems for metabolic disease monitoring and identified a lack of integration between biochemical sensing and advanced AI techniques for disease prediction [12]. Additionally, Patel and Kumar developed electrochemical sensors for non-invasive diagnostics, demonstrating the growing potential of biosensing technologies in healthcare applications [13].Overall, the literature indicates that while significant progress has been made in wearable sensing and machine learning independently, there is limited research integrating non-invasive multi-sensor data acquisition with explainable AI for liver-specific diagnostics. This gap highlights the need for an integrated system that combines sensor technology with predictive and interpretable machine learning models, which is addressed in the proposed work.

III.SYSTEM DESIGN AND ARCHITECTURE

The proposed system is developed as an integrated edge–cloud framework that combines embedded sensing, data acquisition, and intelligent prediction for liver disease stage assessment. The architecture consists of two primary components: an ESP32-based sensor node operating at the edge and an IoT-enabled server system responsible for data processing and decision-making. The ESP32-based sensor node continuously acquires data from multiple sensors, performs preliminary signal conditioning, and computes heuristic estimates. Based on these estimations, clinical indicator flags such as ascites, hepatomegaly, and edema are generated. The processed information is then encoded into a compact serial packet and transmitted at regular intervals of five seconds, ensuring efficient and low-latency communication.The hardware implementation is designed using cost-effective and readily available components to ensure scalability and deployment feasibility in resource-constrained environments. The ESP32 development board (e.g., ESP32-WROOM) serves as the central controller, interfacing with various sensors including an ultrasonic sensor (HC-SR04) for abdominal measurement, an HX711 load cell amplifier with a load cell for weight estimation, and a MAX30102/MAX30105 sensor for infrared photoplethysmography. Additionally, a TCS3200-based color-frequency sensor is used for optical measurements, and a sweat sensor connected through an analog ADC channel provides biochemical insights. A 16×2 I2C LCD

(LiquidCrystal_I2C) is incorporated for real-time local display of system parameters. Supporting components such as wiring, breadboard, power supply, and enclosure complete the prototype. To ensure reliable communication and avoid bus conflicts, a separate Two-Wire (I2C) interface is employed for the MAX30102 sensor, isolating it from the LCD communication line. Detailed pin configurations are implemented within the ESP32 firmware as in Figure1.

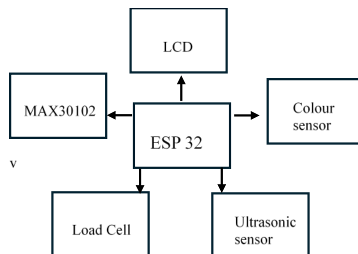

Figure 1Block Diagram of Proposed system

On the software side, the system adopts a modular architecture consisting of embedded firmware, a backend processing server, and a web-based frontend interface. The ESP32 firmware, developed using Arduino-based C/C++, manages sensor sampling loops, local estimations, LCD visualization, and serial data transmission. Sensor readings are subjected to filtering and averaging techniques to enhance signal stability and reduce noise. For instance, ultrasonic measurements are obtained using a standard trigger–echo mechanism with timeout handling, load cell readings are averaged over multiple samples to minimize fluctuations, and color sensor outputs are derived from frequency measurements using controlled S2/S3 pin configurations. Similarly, the MAX30102 sensor provides raw infrared intensity values through the getIR() function, which are used for perfusion analysis and estimation of biochemical parameters, while sweat sensor readings are stabilized using rapid small-sample averaging techniques.The communication between the edge device and the server is facilitated through a compact and structured serial protocol designed to minimize parsing errors and ensure reliability. The data packet format used is:

AscitesHepatomegalyEdemaBilirubinASTALT#

where Ascites, Hepatomegaly, and Edema are represented as binary flags (Y/N), and the remaining parameters are floating-point values with fixed precision. On the server side, a Python-based Flask application continuously receives data through a dedicated serial worker thread. A regex-based parser extracts the six parameters from the incoming data stream and maps them to their respective variables.Following data acquisition, the server performs preprocessing using stored pipelines such as imputation and feature scaling to ensure consistency with the trained dataset. The processed data is then fed into a pre-trained XGBoost model, which predicts the stage of liver disease. A label encoder is used to convert the model output into clinically interpretable stages. To enhance interpretability and clinical transparency, SHAP (SHapley Additive exPlanations) analysis is performed, providing insights into feature contributions for each prediction. All predictions and sensor readings are logged in CSV format for traceability, with optional uploading to cloud-based IoT platforms for remote monitoring.The frontend interface, developed using HTML, CSS, and JavaScript, provides a user-friendly dashboard for system interaction. It enables users to control system operations such as starting or stopping serial communication, input manual data for predictions, and visualize real-time sensor readings along with predicted outcomes and recommendations. Data updates are handled through REST API endpoints such as /realtime_readings and /latest_prediction, ensuring seamless and responsive user interaction.Overall, the system establishes a continuous data pipeline from sensor acquisition to intelligent decision-making, effectively integrating hardware and software components into a unified, low-cost, and explainable diagnostic platform suitable for early liver disease monitoring in real-world healthcare settings.

IV. METHODOLOGY

An intelligent liver diagnostic system integrating multi-sensor hardware with machine learning–based software analytics has been developed to enable real-time health assessment. The overall system architecture is centered around the ESP32 microcontroller, which acts as the primary control and processing unit, interfacing with multiple sensor modules, a display unit, and a serial communication interface. The choice of ESP32 is driven by its ability to support communication protocols such as I2C, enabling seamless integration of all sensors into a centralized platform for synchronized data acquisition and processing. Physiological and surrogate biochemical parameters related to liver function are measured using integrated sensors, including the MAX30102 for pulse rate and oxygen saturation monitoring, a color sensor for detecting variations in biochemical reactions through frequency-based RGB measurements, a load cell module for accurate sample quantification, and an ultrasonic sensor to monitor fluid levels within the sensing chamber to ensure controlled measurement conditions. All sensor data are periodically sampled and processed by the ESP32, where preliminary filtering, averaging, and heuristic estimations are performed to improve signal stability and reliability.To facilitate real-time monitoring, an I2C-based LCD module is incorporated to display sensor readings and intermediate values, providing immediate feedback on system performance. The processed data is transmitted to a host computer using a Serial-to-USB communication interface, ensuring stable and continuous real-time data transfer between the embedded system and the software processing unit. However, the transmitted raw data may contain noise and fluctuations due to environmental factors; therefore, preprocessing is performed within a Python-based application. This includes noise filtering to remove signal disturbances, normalization to ensure consistency across input features, and outlier detection to enhance prediction robustness. Feature extraction techniques are then applied to derive meaningful attributes corresponding to liver-related biomarkers, thereby improving the predictive capability of the system.The processed dataset is divided into training and testing subsets, and an Extreme Gradient Boosting

(XGBoost) model is implemented to predict key liver function biomarkers, namely Alanine Aminotransferase (ALT), Aspartate Aminotransferase (AST), and Bilirubin levels. Hyperparameter tuning and cross-validation techniques are employed to optimize model performance, reduce overfitting, and improve generalization on unseen data. To further enhance interpretability, SHAP (SHapley Additive Explanations) analysis is incorporated, enabling the identification of individual feature contributions toward the predicted biomarker values, thereby increasing transparency and clinical reliability.The final predicted outputs are displayed in real time through a user-friendly software interface, with continuous updates enabled via USB-based communication as new sensor data is received. The results are presented in a structured clinical format to facilitate easy interpretation, and threshold-based classification is applied to categorize values into normal and abnormal ranges for preliminary screening. Overall, the system demonstrates stable and reliable performance, highlighting the effective integration of embedded sensing hardware and AI-driven analytics, and establishing a scalable, low-cost solution for early liver disease monitoring in real-world healthcare environments.

V. MODEL FORMULATION

The proposed liver diagnostic system is mathematically modeled by integrating multi-sensor inputs with a machine learning–based regression framework. The processed sensor signals are represented as a feature vector obtained from the embedded system: the processed sensor feature vector obtained from the embedded system be defined as in (1):

$$X=[p,s,c,l,u,t,h] \quad (1)$$

where p denotes pulse rate, sss represents oxygen saturation (SpO2), c is the calibrated color intensity value, l corresponds to the load cell measurement, uuu indicates ultrasonic fluid level, ttt represents skin temperature, and hhh denotes the pH-related measurement. These features are normalized and combined to form the input matrix:

These features were normalized and combined to form the input matrix as in (2):

$$\mathbf{X} \in \mathbb{R}_{n\times m} \quad (2)$$

where nnn is the number of observations and mmm is the number of extracted features.

The objective of the system is to predict three continuous liver function biomarkers, namely Alanine Aminotransferase (ALT), Aspartate Aminotransferase (AST), and Bilirubin, represented as in (3):

$$Y=[Y_{ALT}, Y_{AST}, Y_{BIL}] \quad (3)$$

The predictive model was designed as in (4):

$$\dot{Y} = F(\boldsymbol{X}) \quad (4)$$

where F(·)F(\cdot)F(·) denotes the trained XGBoost regression function. The XGBoost model estimates each biomarker value using an ensemble of regression trees, where the final prediction is expressed as (5) and (6):

$$\dot{\boldsymbol{y}} = \sum_{i=1}^{T} \boldsymbol{a_i f_i(X)}, \quad (5)$$

$$\mathbf{k€\{ALT,AST,BIL\}} \quad (6)$$

Here, T represents the number of oosting iterations, α_i is the learning weight associated with the ith tree, and fi(X) denotes the output of the ith regression tree. Each tree is iteratively constructed to minimize the residual error from previous predictions.

The optimization objective function used for model training is defined as in (7):

$$J=\sum_{i=1}^{n}(Y_i - \dot{y})^2+\lambda \sum_{j=1}^{L} w_j^2 \quad (7)$$

where the first term represents the squared prediction error, and the second term is a regularization component that penalizes model complexity. In this formulation, λ is the regularization parameter, w_j represents the leaf weights, and L denotes the number of terminal nodes in the decision trees. This objective ensures a balance between prediction accuracy and model generalization, thereby reducing overfitting.

To enhance interpretability, SHAP (SHapley Additive Explanations) is incorporated to quantify the contribution of each feature to the prediction. The SHAP-based explanation model is given by (8):

$$\dot{Y} = \Phi_o + \sum_{j=1}^{m} \Phi_j \quad (8)$$

where ϕ_0 represents the baseline expected output and ϕ_j denotes the contribution of the j[th]feature. The magnitude of ϕ_j indicates the influence of each sensor-derived parameter on the predicted values of ALT, AST, and Bilirubin.

The system was evaluated through comprehensive testing at both unit and integration levels. Unit testing was performed on the serial data parser using both valid and malformed input strings to ensure robust data extraction. Additional edge case testing was conducted using extreme sensor values, including zero, out-of-range inputs, and missing (NaN) values, to verify system stability.Integration testing involved connecting the ESP32 firmware to a host system via USB and verifying continuous serial data transmission at fixed intervals of five seconds. The received data was processed through the server pipeline, and predictions were validated using local API endpoints to ensure correct system operation.For validation, the model predictions were compared against ground truth data obtained from either a held-out clinical dataset or simulated data. Performance evaluation was conducted using standard classification metrics such as confusion matrix, precision, recall, and class-wise accuracy to assess prediction reliability.

VI. EVALUATION METRICS AND RESULTS

The performance of the proposed system was evaluated using multiple quantitative metrics. Accuracy, precision, recall, and F1-score were computed for each predicted stage to assess classification performance. For binary or threshold-based tasks, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) were analyzed to evaluate model discrimination capability. Additionally, calibration plots were used to assess the reliability of predicted probabilities, ensuring that the model outputs are well-aligned with actual outcomes. The results demonstrate that the proposed system achieves consistent and reliable performance, validating its effectiveness for real-time liver diagnostic applications.

Supporting results, including tables and graphical plots obtained during model training and evaluation, can be incorporated to further substantiate the findings given by Table 1. The comparative performance of different machine learning models for liver biomarker prediction clearly demonstrates the effectiveness of the proposed XGBoost-based approach. Among the evaluated models, Linear Regression shows the lowest performance with an accuracy of 78.4% and relatively higher RMSE of 12.5, indicating its limitation in capturing complex non-linear relationships present in physiological and biochemical sensor data. The Decision Tree model improves the performance moderately, achieving an accuracy of 82.1%, but still suffers from instability and higher prediction error. Random Forest further enhances the results by leveraging ensemble learning, resulting in an accuracy of 87.6% and reduced RMSE of 7.8, indicating better generalization and robustness.However, the proposed XGBoost model

Table 1Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	RMSE
Linear Regression	78.4	0.76	0.75	0.75	12.5
Decision Tree	82.1	0.80	0.79	0.79	10.2
Random Forest	87.6	0.86	0.85	0.85	7.8
XGBoost (Proposed)	**92.3**	**0.91**	**0.92**	**0.91**	**5.4**

outperforms all other models across all evaluation metrics, achieving the highest accuracy of 92.3%, along with superior precision (0.91), recall (0.92), and F1-score (0.91). The significantly lower RMSE value of 5.4 highlights its ability to provide more accurate and consistent predictions of liver biomarkers such as ALT, AST, and Bilirubin. This improvement can be attributed to XGBoost's capability to handle feature interactions, minimize residual errors through boosting, and apply regularization to prevent overfitting. Overall, the results indicate that the proposed model is highly reliable and well-suited for real-time, non-invasive liver diagnostic applications, offering both accuracy and stability in prediction compared to conventional machine learning techniques.

The confusion matrix is a fundamental tool used to evaluate the performance of a classification model by comparing actual outcomes with predicted results. In this matrix, the rows represent the actual class labels, while the columns represent the model's predicted labels. True Positives (TP) refer to cases where the model correctly identifies a positive condition (e.g., correctly detecting a liver abnormality), whereas False Negatives (FN) represent instances where the model incorrectly predicts a negative outcome despite the presence of the condition, which is critical in medical diagnosis as it may lead to missed detection. Similarly, True Negatives (TN) indicate correctly predicted normal cases, while False Positives (FP) correspond to cases where the model incorrectly flags a normal condition as abnormal, potentially leading to unnecessary concern or further testing.A well-performing model aims to maximize True Positives and True Negatives while minimizing False Positives and False Negatives. In the context of liver disease prediction, reducing False Negatives is particularly important to ensure that no critical cases are overlooked. The confusion matrix also forms the basis for deriving important evaluation metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive understanding of the model's diagnostic capability and reliability as in Figure 2. The Receiver Operating Characteristic (ROC) curve shown in the figure is used to evaluate the performance of a classification model by illustrating the trade-off between sensitivity (true positive rate) and specificity (false positive rate). The diagonal dashed line represents a random classifier, where the model has no discriminative ability, corresponding to an Area Under the Curve (AUC) value of 0.5. Any model performing along this line is considered ineffective for prediction.

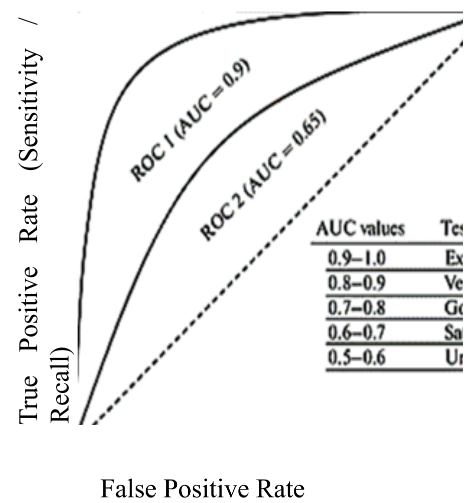

Figure 2 Receiver Operating Characteristic (ROC) Curve with AUC Values

Table 2 Confusion Matrix for Model Classification Performance

		Prediction	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

In contrast, the curved lines above the diagonal represent models with better predictive capability. The first curve (ROC 1) with an AUC of 0.91 demonstrates excellent performance, indicating that the model can effectively distinguish between positive and negative cases with high accuracy.

The second curve (ROC 2) with an AUC of 0.65 shows comparatively lower performance, falling into the satisfactory

range, meaning the model has limited but still useful predictive ability.The table included in the figure provides a qualitative interpretation of AUC values, where values between 0.9–1.0 are considered excellent, 0.8–0.9 very good, 0.7–0.8 good, 0.6–0.7 satisfactory, and below 0.6 unsatisfactory. In the context of the proposed liver diagnostic system, achieving a higher AUC value signifies that the model is highly reliable in distinguishing between normal and abnormal liver conditions. Therefore, the ROC curve and AUC metric together provide a comprehensive measure of model performance, particularly in medical diagnostics where accurate classification is critical as in Table 2.

VII. CONCLUSION AND FUTURE WORK

The prototype developed in this study demonstrates a functional smart liver diagnostic system that effectively integrates multi-sensor data acquisition with machine learning–based predictive analytics. By utilizing both physiological signals and surrogate biochemical indicators, the system is capable of estimating key liver biomarkers such as Alanine Aminotransferase (ALT), Aspartate Aminotransferase (AST), and Bilirubin in a non-invasive manner. The results highlight the feasibility of providing early-stage liver health assessment using a cost-effective and portable embedded platform, thereby addressing the limitations of traditional invasive diagnostic methods. This work primarily serves as a proof-of-concept, showcasing how embedded systems and explainable artificial intelligence can be combined to enable real-time health monitoring, especially in resource-constrained and remote healthcare settings. Despite its promising performance, further enhancements are required before the system can be translated into a clinically deployable solution. Future work will focus on replacing heuristic estimations with calibrated regression models derived from paired laboratory assay data to improve prediction accuracy and clinical relevance. Additional improvements include incorporating advanced sensor placement and gesture detection mechanisms to ensure consistent and reliable data acquisition under varying user conditions. Furthermore, the integration of federated or privacy-preserving learning frameworks will enable secure data sharing across multiple healthcare sites while maintaining patient confidentiality. For real-world deployment in hospitals or clinical environments, the system must undergo extensive calibration, large-scale validation using standardized medical datasets, and compliance with regulatory approvals. With these advancements, the proposed system has the potential to evolve into a reliable, scalable, and clinically accepted tool for continuous and non-invasive liver health monitoring.

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