Development of an AI-Driven Multi-Sensor Health Monitoring System for Real-Time Physiological Analysis and Insight Generation

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***Abstract*—The existing healthcare systems are based on a limited number of physiological parameters, such as the body, temperature, the pulse rate and the body weight, as the initial screening parameters. Even though these indicators provide an approximate. evaluation, they do not reflect the more in-depth changes of physiological variations that are associated with dangers of underlying health. problems, leading to delayed diagnosis and reduced effectiveness of preventive measure The present paper describes an AI-based multi-sensor health monitoring system that will create advanced physiological information through non-invasive measurements. The system combines photoplethysmography (PPG) based on the infrared, temperature, and voltage-based signal detection to obtain the most important health indicators such as heart rate, oxygen saturation, perfusion index, level of hydration, stress index, and blood pressure dynamics. Filtering, normalization and feature extraction are signal processing methods used to guarantee reliable interpretation of the data. It uses a hybrid multi-model AI structure, so that a multi-domain classification and baseline estimation is done using a Random Forest model, and high-accuracy blood pressure prediction is done using a LightGBM model. These models are linked together in a cascaded chain of inferences to improve the predictive accuracy. Also, a Large Language Model (LLM) is introduced to transform the numerical results into structured topics that can be analyzed by humans based on clinical interpretation. The suggested system has a high predictive accuracy and has a low computational overhead, allowing real-time deployment of the edge and offering a scalable and cost-efficient solution to intelligent and preventive healthcare monitoring.**

***Index Terms*—IoT-based health monitoring, multi-sensor systems, photoplethysmography (PPG), physiological signal processing, artificial intelligence, data fusion, real-time health analytics**

I. Introduction

The contemporary medical systems are largely dependent on fundamental phys. iological measures, including body temperature, pulse rate, and body weight as first patient assessment. While the following parameters give a rough idea of one. state of a person, they do not record more physiological. changes related to early-age health risks including dehydration, heart defects and stress-induced. Where there is congested clinical setting, like in a hospital. and emergency care units, in most cases, emergency care is about speedy patient screening. carried out on a restricted physiological backdrop. As a result, health co-morbidities might go undiagnosed. to diagnostic blindness and time-losing medical care. Thus, the demand to have integrated health is increasing. physiolog monitor systems with the ability to analyze a variety of physiolog. ical signals to offer in more comprehensive. insights [2], [4].

Recent developments on the Internet of Things (IoT) technology. The development has been possible through gies and embedded systems. of small and live health-to-be health monitoring platforms. These systems use non-invasive sensors or wearable sensors to. incessantly gain physiological messages like photo. plethysmography (PPG), temperature, and electrical activity. Nevertheless, most of the existing IoT-based solutions are concerned with. single parameter monitoring and are not good data fusion. it contains mechanisms, restricting their capacity to produce meaningful high. level health insights [3], [7].

Photoplethysmography (PPG) has become a popular emerging application of photoplethysmography. non-invasive cardiovascular monitoring technique adopted. because it is cheap and easy to incorporate into embedded. devices. It allows obtaining major physiological. heat rate, oxygen saturation and perfusion metrics. index. Nonetheless, PPG signals are very sensitive to. noise and motion artifact, which demand high signal processing. methods of credible interpretation [9], [11].

The concept of artificial intelligence (AI) integration in healthcare. has greatly enhanced the health monitoring ability. complex physiological data analysis systems and generation. predictive insights. Machine learning models are able to distinguish. patternity of multi-dimensional datasets and approximate. like blood pressure, level of hydration and stress. index. Nonetheless, numerous current AI-based solutions are based on. on single-model architectures and need big-scale cloud. they can be updated and used in real-time, making their use restricted to based processing. environments [1], [12].

This study will propose a research to overcome these limitations. Reality-fashioned multi-sensor health surveillance system based on AI. grates acquisition of physiological signals, real-time process. and multi-model intelligence. The systems are also unlike traditional systems. the suggested architecture resorts to a mixed strategy com. bining Classification with LightGBM, based on random forests. clinical, regression, and a Large Language Model (LLM). interpretation. This is a multi-model design that allows task-specific. optimization, in which classification, regression, and contextual are used. specialized components deal with reasoning [8], [4].

The system makes use of infrared PPG signals, multi-point tem. cap voltage based signal acquisition and per temperature sensing. Ture cardiovascular, thermal and bioelectrical properties of. the human body. Filtering is used to process these signals. extract features and to derive the features used by normalizing to obtain. significant parameters like the heart rate variability, oxygen. stress index, level of hydration, and saturation [11], [16].

One of the contributions of this work is the integration of. A series of inference pipes, with the predictive outputs of predictive. Downstream analysis of models is re-used. Further Besides, a locally deployed LLM can be included to provide auto. structured clinical reporting mated generation changing raw numerical forecasts into understandable health forecasts. This data fusion via multi-sensors, edge based. processing and multi-model intelligence offers a scalable. and economical preventive healthcare in real-time. monitoring [5], [25].

II. Related Work

A. PPG-Based Health Monitoring

Photoplethysmography (PPG) has been extensively used in cardiovascular monitoring being a non-invasive method of measuring changes in blood volume via optical sensing. It is a procedure that monitors the heart rate during systolic and diastolic cycles and makes it possible to observe irregular heart activity . It can be used to estimate the vital physiological parameters, including heart rate, oxygen saturation, that are vital when using real-time health monitoring solutions . PPG is a low-cost, wearable and portable device because of its affordability, making it a common component of wearable and IoT health systems (Larson, 2016) [7], [10].

The most recent research has been aimed at enhancing the quality of PPG signals with the assistance of the high-level signal processing algorithms, such as peak detection, filtering, and noise reduction schemes. Though these techniques improve the signal quality, majority of the existing systems operate on single dimensions of physiological data and do not extrapolate higher dimensions of health underpinning in the available data . As a result, our overall comprehension of physiological conditions has not yet been developed and is not contextualized [9], [19].

B. Multi-Sensor Health Monitoring Systems (MSHMS)

Multi-Sensor Health Monitoring Systems (MSHMS) The chronicle of the time spent on the development of the healthcare technology has led to the introduction of multi-sensor systems that integrate the information of multiple physiological sources to provide a more comprehensive assessment of the health condition of a user. These systems combine the different sensor inputs including temperature sensors, motion sensors and biosignal acquisition modules to improve the monitoring accuracy as well as coverage.

Nevertheless, the current multi-sensor platforms do not implement an appropriate data fusion strategy and mostly handle sensor data autonomously. This constrains their ability to encode several physiological signals into each other. Such a lack of integration decreases the capability of the system to create useful insights and allows not deriving complex physiological relationships in the various areas of health [24], [15].

1) Machine Learning (ML) and Artificial Intelligence (AI) Health Monitoring Methods: Machine learning (ML) and artificial intelligence (AI) Health monitoring methods are much more analytical AI has greatly expanded the analytical ability of health monitoring machines and systems, including the ability to identify patterns and make predictions without any human intervention . The machine learning algorithms are capable of processing large volumes of physiological data to estimate the parameters (e.g., the blood pressure), identify abnormalities, and predict the possibility of the disease occurrence [23], [21].

Despite these advancements, the majority of present AI-based systems are based on single-model systems. There is a tendency to use one model to achieve multiple complex tasks and, accordingly, to ensure poor performance . In addition, these systems are often dependent on cloud-computation which adds latency and reduces applicability to real-time applications in resource constrained environments [5], [20].

2) Signal Processing: Signal processing plays a crucial role in biomedical systems so as to provide accuracy, reliability, and noise-free biomedical measurements [16]. One of the most common techniques that are used to process physiological signals so as to ensure a stable and meaningful representation of data is filtering, normalization and feature extraction, among others [17].

However, most existing systems consider signal processing as a distinct preprocessing stage instead of a component of a high-level predictive model. Through this division, the overall system effectiveness is reduced and the ability of the system to perform real-time analysis and decision-making is limited.

C. Research Gap

Based on the review of available literature, it is clear that the advancements have been achieved in the single spheres of PPG-based monitoring, multi-sensor systems, AI-based prediction, and signal processing methods. Nevertheless, there is still a gap of a singular framework that has incorporated all these elements into one intelligent system.

The variants of most of the existing solutions are either single parameter estimation or the computationally intensive models that cannot be deployed in real time. Moreover, little research has been conducted on integrating various specialized models with context reasoning processes like large language models to interpret clinical data.

Consequently, the multi-sensor data acquisition, efficient signal processing, multi-model machine learning, and intelligent report generation system is required, which will give a complete and interpretable health understanding in real time.

III. System Architecture

The proposed system is built as a multi-layered system that can acquire, process, and intelligently interpret physiological signals in real-time. It combines sensing, signal processing, and multi-model inference in a single framework to generate an all-around health insight [12]. The architecture is split into three main layers: the sensing layer, the processing layer and the intelligence layer. It is also equipped with a multi-model intelligence framework to promote the accuracy and interpretability of prediction.

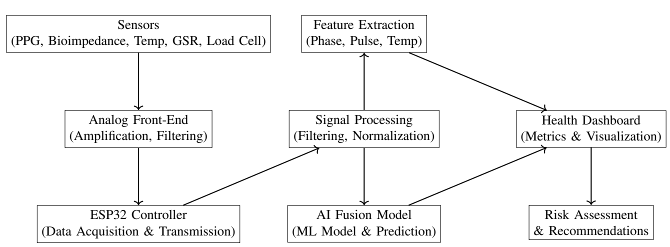

Fig. 1. System flow diagram representing sensing, processing, and clinical decision layers.

System Architecture of the Proposed Health Monitoring System

A. Sensing Layer

The sensing layer is the one that gets the physiological information of the user by means of non-invasive sensors. The system uses infrared photoplethysmography (PPG) sensor to record cardiovascular signals to obtain heart rate, oxygen saturation, and perfusion index.

The concept of multi-point temperature sensing is used in which the thermal variations in the body are captured by using infrared sensors, which offer better accuracy than single sensations.

Also there is the use of a voltage sensing module to acquire bioelectrical features of the body. These indicators are used to approximate physiological variables of hydration level, stress index, and trends of blood pressure [6].

The benefit of this multi-sensor arrangement is that this coverage of physiological aspects is extensive and also the diversity of such data enhances the stability of the monitoring system [4], [7], [24].

B. Processing Layer

Processing layer converts raw sensory data to meaningful and structured features. Physiological signals are also very noisy and prone to external interference, thus signal conditioning methods like filtering and normalization have been used to improve quality of data.

The step of feature extraction is then carried out in order to extract important physiological signals. To illustrate, the heart rate and heart rate variability are computed through peaking of PPG signals, and the voltage and temperature are processed in order to identify the patterns that may indicate physiological conditions [9].

The system incorporates signal preprocessing and feature extraction, thus making sure that the input to the intelligence layer is correct, stable and predictable [16], [17].

C. Intelligence Layer

The layer of intelligence brings together the processing features into actionable health insights. It uses machine learning models to process multi-domain physiological data and provide predictive outputs that include blood pressure prediction, hydration, stress classification, and disease risk classification [21].

This layer is used to do multi-parameter data fusion which is used in deriving higher-level measurements of health unlike the traditional systems which are only based on single-parameter analysis, thus enhancing the overall interpretability of the system [25].

D. Multi-Model Intelligence Framework

The system will be implemented with a hybrid multi-model architecture, which is a combination of several specialized models to improve its performance and scalability.

The former is a Random Forest-based ensemble model, which is used to classify and baseline regress, such as heart disease risk, lung risk, and initial blood pressure estimation across multi-domain. Random Forest models can be effectively applied in the context of small and heterogeneous clinical data because of their resistance against overfitting and robustness [3].

The second is a LightGBM regression model with high accuracy in estimating systolic and diastolic blood pressure on the basis of multi-dimensional physiological characteristics. LightGBM and other gradient boosting algorithms are used in large-scale tabular data and they are very effective with high predictive accuracy [5].

The third one is a Large Language Model (LLM) that prepares systematic clinical reports based on the summative outputs. of the forecasting models. This model transforms numerical. guesses into medical narratives that can be comprehended by users. to aid in decision-making. These models are deployed as a cascaded pipeline with the help of which the. outputs of the previous models are used as inputs in the later stages. The tasks and their optimization can be optimized with this architecture. enhances the accuracy of prediction and contextualization

E. Hardware Implementation

The hardware in the system is embedded and is as follows. in charge of physiological data in real-time and processing. The ESP32 micro- is the main processing unit. controller that does data acquisition, preprocessing and communication.

The system incorporates the following elements:

- MAX30102 PPG Sensor: This sensor has a sampling rate 400 Hz of 400 Hz to measure heart rate, SpO2 and perfusion index.
- MLX90614 Infrared Temperature Sensor: A non- contact sensor to measure body temperature accurately measurement.
- AD8232 Signal Acquisition Module: This is used in capturing further analysis in terms of bioelectrical signals (as depicted in Fig. 1).
- Analog Front-End: Provides efficient ap- sampling processing impedance-related about 250 Hz signals.

The bioimpedance signal is sampled over a latency of 200 ms, consisting of about 50 ADC samples, allowing the estimation of RMS voltages to be stable.

All sensor data are real-time processed and sent to the computational layer to be further analyzed, making sure that it is low latency and effective performance of the system [22].

F. Overall System Flow

The system pipeline is systematic in which Immediate sensor information is received and thereafter it is preprocessed. and features are distilled out. The resultant processed data is then inputted into a multi-model inference pipeline where it is classified, regression and contextual interpretation are carried out in order.
Finally, the results are availed to the user as nu- Artificial intelligence and the use of merical measurements and artificial intelligence in clinical. information. A modular and layered architecture such as this ensures a guarani- The scalability, resilience and real time execution of tees, and consequently, the system can be used in applications that involve continuous health monitoring.

IV. Methodology

The suggested system is based on the hybrid computational combines the physiological signal processing, architecture. deterministic modeling, and the multi- inference. model machine learning. The methodology is organized into steps to follow and these include the signal acquisition, the the feature extraction, predictive modelling, preprocessing, and the clinical meaning [16].

A. Physiological Signal Processing

Photoplethysmography (PPG) measurements of the infrared sensor are processed to get cardiovascular features. The PPG waveform is detected using peak detection to determine. interbeat intervals:

$$RR_k = (p_{k+1} - p_k) \cdot T_s \tag{1}$$

where p_k represents detected peak indices and T_s is the sampling period.

Heart Rate Variability (HRV) is computed using the Root Mean Square of Successive Differences (RMSSD):

$$RMSSD = \frac{1}{N-1} \sum_{k=1}^{N-1} (RR_{k+1} - RR_k)^2 \times 1000 \tag{2}$$

This metric is used for stress estimation and autonomic nervous system analysis [9].

B. Oxygen Saturation Estimation

Oxygen saturation is estimated using the ratio of red and infrared light intensities obtained from the PPG sensor. The ratio parameter is defined as:

$$R = \frac{Red}{IR} \tag{3}$$

The SpO_2 value is computed using an empirical linear model:

$$SpO_2 = 110 - 25R \tag{4}$$

This simplified formulation reduces computational complexity while maintaining acceptable accuracy for real-time embedded applications [10].

C. AI Models and Algorithms

The suggested system has a hybrid multi-model AI architecture based on machine learning, signal processing, and natural language processing methods to allow precise and explainable health forecasts [21].

1) Random Forest (Classification + Baseline Estimation): In the first inference stage, a Random Forest ensemble model is applied when performing multi-domain classification, which includes risks of heart disease, estimating risks of lungs, and approximating baseline blood pressure. Random Forest combines the results of several decision trees to enhance the performance over generalization [3].

It is also especially applicable in heterogeneous physiological data, and is resistant to overfitting in small clinical data [20].

2) LightGBM (Blood Pressure Prediction Regression Model): High-precision systolic and diastolic blood pressure regression is done with a LightGBM model. Gradient boosting methods are used to minimize the error of prediction in an iterative way and are very effective in nonlinear physiological relationships [5].

The model incorporates multi-dimensional physiological factors (heart rate, SpO_2, temperature, HRV, BMI), age, and gender, which allow the cardiovascular dynamics to be modeled accurately [5].

3) Cascaded Inference Pipeline (CIP): The system has a cascaded mechanism of inferences where the results of the Random Forest model are employed as input features in the LightGBM model. This cross-model dependency has the benefit of making features rich and predicting better [3].

These multi-stage architectures have been demonstrated to be superior to single-model predictive tasks in multi-faceted physiological predictions [20].

4) Signal Processing Algorithms (Pre-AI Stage): Prior to machine learning model application, a number of signal conditioning and feature extraction methods are used to process physiological signals. They are peak detection in the analysis of heart rate variability, exponential moving average (EMA) filter, RMS calculation of the signal and noise reduction approaches [16], [17].

Such preprocessing steps can stabilize the input features, make them reliable and appropriate to the downstream machine learning processes [16].

5) Large Language Model (LLM - Llama 3.2): The final stage is referred to as the conversion of numerical predictions into structured clinical insights, which is achieved by a Large Language Model (LLM). The model produces human-readable health reports through the interpretation of multi-domain outputs of physiology [21].

It is an interpretable method that improves the distance between the predictions of an AI and the understandable medical feedback provided to the user [23].

D. Bioimpedance-Based Hydration Modeling

Bioimpedance characteristics are estimated using RMS voltage measurements derived from the signal acquisition module.The elements of resistance and reactance are calculated as:

$$R = 500 + 12 \cdot V_{RMS} \tag{5}$$

$$X_c = 180 \cdot V_{RMS} + 0.001 \cdot IR \tag{6}$$

Total Body Water (TBW) can be estimated as:

$$TBW = 62.1 + 0.001 \cdot R + \epsilon \tag{7}$$

where $\epsilon \sim \mathcal{N}(0, 0.05)$. Bioimpedance analysis provides understanding of hydration and cell health [6].

E. Temperature Estimation

The system makes use of two temperature sensors to improve stability. The average temperature is computed as:

$$T_{avg} = \frac{T_1 + T_2}{2} \tag{8}$$

In order to cover the variation in skin-to-core, an empirical offset is applied:

$$T_{final} = T_{avg} + 2 \tag{9}$$

This modification enhances the approximation of internal body in non-invasive measurements, temperature.

F. Signal Filtering and Conditioning

Several physiological measurements should be taken to guarantee good physiological measurements filtering methods are used on sensor modalities. A temporal threshold filter is used to validate heart rate measurements:

$$300 \text{ ms} < \Delta t < 2000 \text{ ms} \tag{10}$$

$$HR = \frac{60000}{\Delta t} \tag{11}$$

An exponential moving average (EMA) filter is applied to extract the DC component:

$$DC_n = 0.95 DC_{n-1} + 0.05 x_n \tag{12}$$

The AC component is derived as:

$$AC = |x_n - DC_n| \tag{13}$$

In the case of impedance signals, RMS filtering is used:

$$V_{RMS} = \frac{1}{N} \sum (x_i')^2 \tag{14}$$

These methods minimize noise and enhance the stability of signals for downstream processing [17].

G. Model 1 – Multi-Domain Risk Model (Random Forest)

The first inferential step uses a Random Forest ensemble to take care of multi-domain classification as well as baseline regression problems. The model is used to assess the risk of heart disease, lung risk and initial blood pressure by utilizing clinical and physiological characteristics.

To be classified, predictions are aggregated by the Random Forest using several decision trees:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{15}$$

where $h_t(x)$ represents individual tree predictions.

Random Forest is selected because it is very strong at working with heterogeneous data and able to be generalized with small clinical data [3].

H. Model 2 – Blood Pressure Prediction Model (LightGBM)

The second stage employs a LightGBM regression model for high-precision estimation of systolic and diastolic blood pressure.

The input feature vector is defined as:

$$x = [HR, T, SpO_2, Age, Gender, W, H, HRV, BMI] \quad (16)$$

The outputs are:

$$\hat{SBP} = f_{sys}(x), \quad \hat{DBP} = f_{dia}(x) \quad (17)$$

The model minimizes mean squared error:

$$L = \frac{1}{N}\sum(y - \hat{y})^2 \quad (18)$$

Gradient boosting can model nonlinear relationships with physiological data correctly, and thus it can be applied to large-scale regression problems [5].

I. Cascaded Inference Mechanism

The system employs a cascade pipeline in which the outputs are used. of one model are used as the inputs of the other models. As a prediction of blood pressure with Model 1 is employed. as an input feature in the classification of the disease. This inter-model dependency provides features with enhanced functionality. ability to make good prediction on account of its alinity and improves prediction. indirect physiological prediction.

J. Model 3 – LLM-Based Clinical Report Generation

The last step involves the use of a Large Language Model (Llama 3.2) to produce format clinical reports. The model uses inputs that are the summation of the outputs of the previous stages and are represented by the forecasted blood pressure and the disease risk scores and the mean physiological parameters.

The inputs made to the LLM generate context-sensitive medical texts, and enable one to process multi-domain data. This methodology will fill the gap between the numerical prediction and clinical information that are understandable to a human.

K. Derived Physiological Metrics

Other physiological parameters are calculated in the following way:

$$BMI = \frac{W}{H^2} \quad (19)$$

$$FFM = \frac{TBW}{72} \times W \quad (20)$$

$$BMR = \begin{cases} 10W + 6.25(100H) - 5Age + 5 & \text{Male} \\ 10W + 6.25(100H) - 5Age - 161 & \text{Female} \end{cases} \quad (21)$$

These derived measures give additional information about metabolic and physiological conditions.

V. Dataset and Training Setup

The machine learning model was trained with a synthesized approximately 200,000 sample dataset, designed to model physiologically real relationships among input parameters and cardiovascular outputs.

Both samples contain the characteristics of heart rate, oxygen saturation, body temperature, age, gender, weight, height, heart rate variability (HRV), and body mass index (BMI). The data was divided into:

- 90% training data
- 10% testing data (20,002 samples)

Man-made systolic and diastolic blood pressure labels were produced based on physiologically inspired linear programs using Gaussian noise, which allows controlled training.

LightGBM framework was used to train the model.

- 1000 boosting iterations
- learning rate of 0.05
- maximum tree depth of 10

The training goal reduces the mean squared error (MSE), it is necessary to guarantee the correct regression performance.[3], [5].

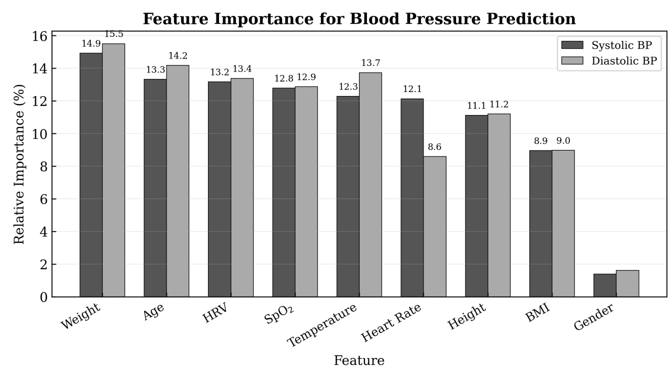

Fig. 2. Feature importance for blood pressure prediction using the LightGBM model. Age and weight are identified as dominant predictors, followed by HRV and temperature.

The model assigns higher importance to age and weight, aligning with established physiological understanding of blood pressure determinants.

VI. Results and Performance Analysis

A. Experimental Setup

The proposed system was tested with a test dataset of 20,002 samples (around 10% of the total dataset of about 200,000 samples). The criterion is on the accuracy of regression, predictive consistency and robustness in varied physiological circumstances. The entire experimentation was carried out based on sensor derived and preprocessed physiological features, according to the methodology in [12].

B. Prediction Accuracy

The system has shown great regression accuracy in the prediction of systolic and diastolic blood pressure with LightGBM model, which is suitable to handle large-scale tabular data regression tasks [5].

TABLE I
REGRESSION PERFORMANCE METRICS

Metric	Systolic BP	Diastolic BP
MAE	1.62 mmHg	1.21 mmHg
RMSE	2.03 mmHg	1.52 mmHg
R^2	0.977	0.952

The metrics of regression performance described in Table I proves the high predictive power of the suggested LightGBM model to estimate systolic and diastolic blood pressure. The value of the Mean Absolute Error (MAE) of 1.62 mmHg (SBP) and 1.21 mmHg (DBP) implies that the model generates predictions with very low average error between the model and actual values and this is well within the clinically acceptable range.

The values of the root mean square error (RMSE) of 2.03 mmHg and 1.52 mmHg, similarly, show that a big error in prediction occurs infrequently, which means that the model has a stable behavior even when the physiological measurements are altered. The value of coefficient of determination (R 2) of systolic and diastolic pressure (0.977 and 0.952, respectively), indicates that the model accounts more than 95 percent of the variation in the data.

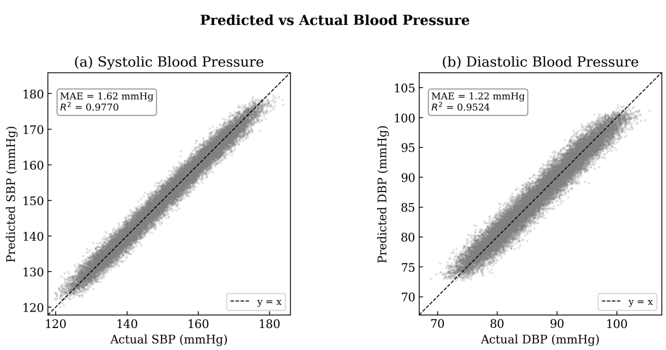

Fig. 3. The (a) systolic and (b) diastolic predicted v/s actual blood pressure values. The very high prediction accuracy is shown by the good alignment along the y = x diagonal.

The scatter plots (Fig. 3) show a good linear relationship between the predicted and actual values with very less deviation over the ideal line of a diagonal. This shows the usefulness of the regression model in representing nonlinear physiological relationships.

The error distribution (Fig. 4) is almost a Gaussian shape with the center of mass at zero, which implies that the model predictions are biased and have low variance among various samples [17].

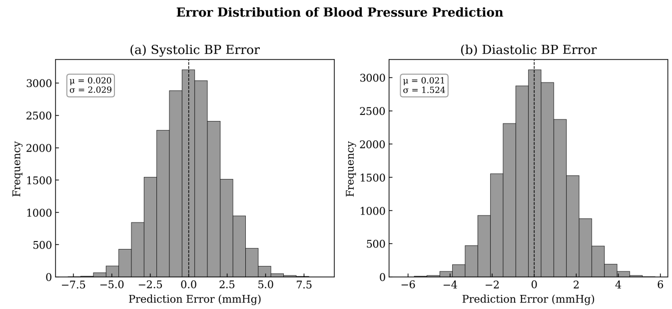

Fig. 4. Error distribution of (a) systolic and (b) diastolic blood pressure predictions. The near-zero mean and narrow spread indicate low bias and high consistency.

TABLE II
TOLERANCE-BASED ACCURACY

Tolerance	SBP Accuracy	DBP Accuracy
±3 mmHg	86.01%	95.08%
±5 mmHg	98.69%	99.92%
±10 mmHg	100%	100%

C. Tolerance-Based Accuracy

Table II presents the accuracy analysis of the predicted blood pressure values based on tolerance, which examines the clinical reliability. The model predicts systolic pressure with an 86.01

The tolerance at the tolerance of ±5 mmHg is much higher at 98.69

The model has 100 percent accuracy at ±10mmHg indicating full coverage within wider clinical tolerance limits. This proves that the system is very reliable in real life screening applications where small variances are tolerated.

The high accuracy within narrow tolerance ranges demonstrates that the model provides clinically meaningful predictions, making it suitable for non-invasive monitoring applications [2].

D. Sample Outputs

TABLE III
SAMPLE MODEL OUTPUTS

HR	SpO_2	Age	SBP	DBP	Stress
72	98.5	25	131.2	77.6	Medium
88	97.1	50	146.4	84.7	High
65	96.8	70	160.0	93.3	High

Table III demonstrates the sample outputs of the model that are functional in making physiologically plausible predictions of various input conditions. For example:

- A younger person (Age 25) with normal SpO2 has moderate blood pressure and medium levels of stress.
- There are increased systolic and diastolic pressure levels in a middle-aged patient (Age 50), which is consistent with age-related cardiovascular changes.
- A mature person (Age 70) has greater blood pressure and stress level with realistic physiological aging trends.

The outputs demonstrate realistic physiological predictions across different age groups and conditions, highlighting the model's ability to generalize effectively across diverse input scenarios.

E. Model Stability

The model exhibits deterministic behavior with negligible variance across repeated predictions:

$$\sigma_{SBP} = 0, \quad \sigma_{DBP} = 0 \tag{22}$$

This indicates that the model produces consistent outputs for identical inputs, ensuring reliability in real-time monitoring environments.

F. Noise Sensitivity Analysis

The system demonstrates robustness to physiological noise and minor input variations:

- ± 5 BPM variation $\rightarrow < 0.5$ mmHg change in SBP
- $\pm 0.5°$C variation $\rightarrow < 0.6$ mmHg change in SBP

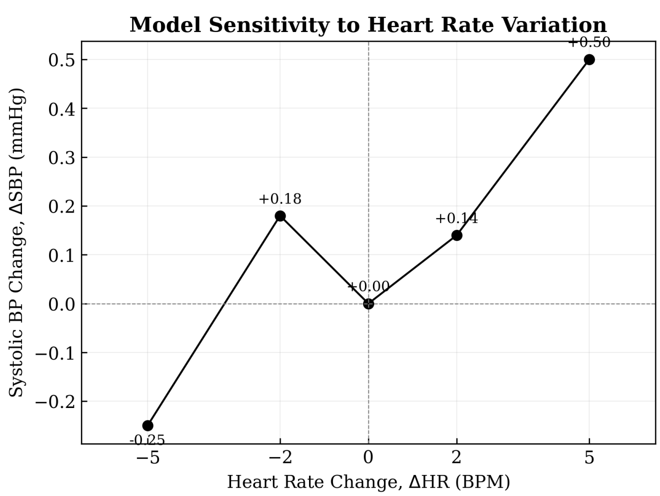

Fig. 5. Model sensitivity to heart rate variation. The small variation in predicted SBP indicates robustness to physiological noise.

As shown in Fig. 5, the model remains stable under small perturbations in physiological inputs, indicating strong resilience in real-world deployment scenarios [17].

G. Observations

The observations that can be made out of the experimental results:

- Age and weight are strong predictors affecting blood pressure estimation.
- The effect of heart rate on systolic pressure is quite small.
- Diastolic pressure is more stable than systolic pressure.
- Multi-sensor data fusion improves prediction consistency and robustness.

H. Validation and Reliability

It should be noted that the blood pressure model is conditioned on the labels that are artificially generated based on physiologically inspired relationships, although they have high predictive accuracy. Although this method allows one to train it and achieve high internal consistency, additional validation with clinical-grade datasets and medical devices is required to determine real-world consistency and clinical applicability [2], [5].

I. Comparative Analysis

In order to assess the efficiency of the suggested strategy, the work of the LightGBM-based regression model was compared to that of a traditional baseline model, which is Linear Regression. The reason is that Linear Regression is a highly popular reference model to estimate physiological parameters because it is easy to use and interpret [5].

TABLE IV
COMPARISON WITH BASELINE REGRESSION MODEL

Model	MAE (SBP)	RMSE (SBP)	R^2 Score
Linear Regression	4.85 mmHg	5.72 mmHg	0.82
Proposed LightGBM Model	1.62 mmHg	2.03 mmHg	0.977

Table IV provides a comparative analysis of the proposed LightGBM model with a traditional baseline of Linear Regression. The outcomes show clearly that there was a great improvement in terms of performance in all metrics.

Compared to 4.85 mmHg (Linear Regression) the MAE is 1.62 mmHg (LightGBM), which is a decrease of about 66%. Correspondingly, the RMSE value drops by 5.72 mmHg to 2.03 mmHg, which means that the prediction is more stable.

R 2 gets to 0.977 as compared to 0.82 and this goes to show that the proposed model is much more effective in capturing the nonlinear physiological relationships as compared to linear methods.

The findings clearly show that the proposed LightGBM model is much more effective as compared to the introduced Linear Regression model in all evaluation figures. The decrease in the mean error of absolute (MAE) is an indication of better prediction accuracy and the increased score in R 2 shows the better fit of the underlying physiological relationships.

The excellent result of LightGBM is explained by the possibility of modeling nonlinear relationships between various physiological characteristics that include heart rate, temperature, HRV, and body composition. Linear Regression, on the other hand, assumes a linear dependence between input characteristics and output variables, which cannot represent the nonlinear character of cardiovascular dynamics.

Moreover, the gradient boosting applied in LightGBM progressively reduced the error of prediction byadding several weak learners, leading to the overall increase of generalization and noise resistance [5]. It is especially crucial in physiological data, where there is often variability and noise in measurements.

1) Comparison with Single-Model Architectures: Traditional health monitoring systems typically rely on a single predictive model to estimate physiological parameters. Such approaches tend to be unable to balance precision and interpretability, particularly in the case of multi-domain data.[20].

The system employs a multi model system comprised of two machine learning models and a single language model: Random Forest: It is employed in classification and baseline.

- Random Forest is used for classification and baseline estimation
- LightGBM is used for high-precision regression
- LLM is used for contextual interpretation

This division of labor enables specialization of each of the models in a particular work, which enhances better performance and scalability of the overall system. In-Cascaded architecture as well enhances the precision of predictions by allowing intermediate configured outputs to be used as enriched feature inputs by the following models.

2) Comparison with Existing Approaches: The current IoT-based health monitoring devices are mostly centered on the estimation of a single parameter or use cloud-based computational analysis. Despite the fact that such systems do offer basic monitoring, they are frequently not real-time interpretable and multi-domain.

The proposed system is different than the current methods in the following aspects:

- Combining data between several sensors to permit a detailed analysis of physiology.
- Edge-based processing to aid real-time inference with low latency.
- Multimodel combination of machine learning models to optimize tasks.
- Addition of Language Model Large to generate clinical reports automatically.

All these enhancements make the system more realistic and applicable to the real-world performance and predictive accuracy, as well as, in the context of preventive healthcare.

VII. Comparison with Existing Work

We compared our system to the existing research in the sphere of IoT-based physiological analysis and health monitoring. The majority of traditional systems are oriented to the monitoring of one parameter, heart rate or temperature, and fail to combine the data of various domains. Recent systems have more than one sensor and are more efficient in data gathering but lack intelligent, real-time analysis. Moreover, most healthcare solutions are based on one machine learning model, which restricts their capacity to learn the intricate relationships among physiological measurements.

VIII. Conclusion and Future Work

A. Conclusion

The suggested system introduces a non-invasive health monitoring platform in real-time that combines the multi-sensor data capture, signal processing, and hybrid multi-model AI system to provide a holistic physiological analysis. In contrast to the traditional methods which involve isolated estimation of the parameters, this system integrates the infrared photoplethysmography (PPG), temperature, and voltage-based measurements to obtain useful health indicators, including heart rate, oxygen saturation, perfusion index, hydration level, stress index, and blood pressure cycles. One of the main contributions of the work is the use of a cascaded multi-model intelligence architecture, in which a model based on the Random Forest is used to classify multi-domain and estimate a baseline, and a model based on LightGBM is used to predict blood pressure correctly. Such cooperative communication between models increases the predictive reliability of such models by providing them with the ability to share features and enhance generalization across stages. Also, the incorporation of a Large Language Model (LLM) allows converting numerical results into meaningful structured and human-readable clinical insights and enhances the system interpretability and usability. Experimental outcomes show that there is high predictive performance, low error margin, and consistency in the presence of different physiological conditions. Moreover, the design of the system is an edge-based computation, which provides a low latency rate and minimizes its reliance on the cloud infrastructure, which is helpful in real-time applications in healthcare organizations. Altogether, the suggested solution effectively integrates machine learning, signal processing, and natural language generation into a full-scale and cost-efficient system, which emphasizes the future of multi-model AI systems in the gap between uncoded physiological measurements and useful medical data, to preventive and intelligent healthcare monitoring.

B. Future Work

Although it had good performance, the system that is in place has some limitations that can be overcome in the future. Synthetically generated data based on physiological approximations is used in training the blood pressure model and this might not fully reflect the clinical variability in the real world. The next step in work will be the validation of the system through clinically verified data and medical-grade devices to enhance the reliability and accuracy of the system.

It is possible to increase the number of sensors incorporated in the system, including electrocardiography (ECG), to detect more sophisticated physiological patterns and enhance the level of diagnostic qualities. Also, the chronic health conditions could be detected early by including continuous monitoring and long-term data analysis.

The next improvement can also consist in optimization of the machine learning models to the ultra-low-power edge devices, allowing their use in the wearable and portable healthcare systems. In addition to that, the LLM component can be further promoted to facilitate individualized health advice and multilingual clinical reporting, enhancing its accessibility and usability.

Lastly, combining cloud-based analytics and edge processing may support hybrid designs of large-scale health data analytics, support population-level health information and predictive healthcare uses.

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