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Design of Sentinel Life Jacket Revolutionizing Care Through Data-Driven Insights and Emergency

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Abstract: Patients who have left the Intensive Care Unit (ICU) for the general wards have a high level of risk of experiencing unnoticed clinical deterioration since they are not subjected to round-the-clock monitoring. This paper presents the Sentinel Life Jacket, a smart wearable patient-monitoring device intended to provide real-time monitoring and risk assessment during the post-ICU recovery stage. The system combines the MAX30102 (heart rate and SpO2), MLX90614 (body temperature), and AD8232 (ECG and respiratory rate) sensors, along with an ESP32 microcontroller, to continuously monitor physiological parameters and transmit them wirelessly. The resulting data are also sent to a Flask-based server, where preprocessing methods, such as signal smoothing and noise reduction, are applied to improve signal stability. The machine learning model used is CatBoost to analyse vital parameters and categorise patient risk levels with high predictive accuracy. When abnormal patterns are detected, the system will send real-time alerts to health care professionals, update a live monitoring dashboard, and display important vitals locally on an OLED display. The suggested approach reduces response time and enhances patient safety during post-ICU recovery by continuously monitoring patients and detecting physiological anomalies early. The proposed hospital monitoring system is scalable, affordable, and reliable, using wearable sensing, IoT connectivity, and AI. Evaluation shows that the proposed system actively monitors patients and diagnoses physiological abnormalities, thereby reducing reaction time and improving patient safety after ICU discharge.

Keywords: Post-ICU Monitoring; Wearable System; CatBoost Algorithm; Smoothing Technique; AI in Healthcare; Alert System; Intensive Care Unit; Monitoring Systems; Performance Analysis.

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1. Introduction

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The Intensive Care Unit (ICU) discharges patients to general wards, a crucial yet delicate stage in their recovery. Although patients are discharged from the ICU only after they have acquired some level of clinical stability, there is a huge proportion of physiologically vulnerable patients. Their vital signs may remain irregular until their bodies are over with a life-threatening illness, surgery, injury or infection. Whereas ICU settings are equipped with new real-time monitoring apparatus and specialised medical care, other restrictions are in place in a general ward. Continuous monitoring of heart rhythm, oxygen saturation, respiratory rate, blood pressure, and body temperature is performed in the ICU using high-precision equipment. But in moving the patients to the general wards, this unremitting electronic monitoring is replaced by occasional manual assessment, which is reviewed at regular intervals [3]. This downplaying of surveillance creates a massive surveillance loophole and may mask the initial signs of degradation. The human implications of such a clinical lapse are massive. Observations and research in hospitals consistently show that adverse events rarely occur overnight. The extreme complications are typically accompanied by insignificant physiological alterations that can worsen over time. Initial signs of infection, respiratory depression, cardiac instability, and systemic inflammatory response may include increased heart rate, subtle abnormal respiratory patterns, minimal oxygen desaturation, and low-grade fever [5].

Finally, patients may be compelled to undergo life-threatening consequences due to emergency operations or unplanned ICU hospitalisations, extended stay, or even life-ending consequences in case these early signs are neglected or even revealed later. In addition to the impact on the doctor's health, these incidents increase the burden on the healthcare infrastructure and, consequently, raise medical costs. Therefore, follow-up with regular, evidence-based exercises after ICU discharge is not only preferable but also required to enhance patient safety and healthcare delivery [25]. The challenge is to introduce a degree of vigilance in the general wards within the ICU without adding the complexity or additional cost of the required infrastructure. Traditional bedside monitoring tools are commonly expensive, bulky, and require wiring and a fixed setup. Such systems cannot always be applied to all the post-ICU patients, particularly in healthcare institutions with limited resources. Moreover, patients in recovery require the freedom to be restored and reassured, which may be curtailed by permanent monitoring systems. Consequently, there is a greater need for miniature, portable, and inexpensive devices that can provide sustained physiological control, making the patient more comfortable and flexible. Recent developments in wearable biomedical sensors, the Internet of Things (IoT), and artificial intelligence (AI) have created new opportunities in healthcare monitoring. Wearable devices can now capture physiological signals non-invasively and continuously. Heart rate, blood oxygen saturation, temperature, and even the electrical activity of the heart can also be assessed with fair precision using small sensors [6].

The IoT-based communication structures enable the distribution of collected data via pay-as-you-go wireless data exchanges with centralised or cloud servers, allowing access to and monitoring of the data from remote locations. To a greater extent, machine learning algorithms can be used to analyse multivariate physiological data and determine trends associated with clinical deterioration [9]. Despite technological innovations, most solutions available on the market focus on monitoring, recording, and presenting data. They are also inclined to produce incomplete or poorly processed information, without the forecasting intelligence to determine multi-dimensional risk patterns. In most cases, the only criterion for triggering alarms is the predetermined threshold value. Even though threshold-based systems are easy to use, they are likely to produce false alarms due to temporary variations or sensor noise. The alarm fatigue of the health practitioner can also result from highly prevalent false alarms, which reduce attentiveness and pose a risk to the patient's health. Intelligent predictive models and mechanisms for stabilising outputs are therefore critical for providing reliability in real-world clinical settings [10]. To address these issues, this paper proposes the Sentinel life jacket, a smart wearable patient-monitoring device designed to assist patients in the post-ICU period. Sentinel Life Jacket is a lightweight, ergonomic jacket that combines multiple biomedical sensors. It continuously monitors vital parameters, such as heart rate, oxygen saturation (SpO2), body temperature, electrocardiogram (ECG), and respiratory rate [11].

The sensors built into the design include the MAX30102, which measures heart rate and SpO2; the MLX90614, which detects non-contact temperature; and the AD8232, which acquires ECG signals. These sensors are attached to an ESP32 microcontroller, which performs initial signal conditioning, filtering, and wireless data transmission. Physiological information is transmitted via Wi-Fi to a Flask server for processing and forecasting dangers. Unlike traditional monitoring systems that use a fixed threshold, the Sentinel Life Jacket employs a machine learning-based classification model trained with the CatBoost algorithm. CatBoost is a gradient-boosting ensemble algorithm particularly well-suited to structured healthcare data. It can efficiently handle heterogeneous features and reduce overfitting using ordered boosting frameworks. Correlations between physiological and demographic characteristics classify the patient's state into a category, such as Normal or High Risk [13]. This predictive facility enables deterioration tendencies to be identified at the initial stages, which cannot be done with a single-parameter threshold. Signal variability due to motion artefacts, sensor motion, perspiration, or environmental factors is a major issue in wearable monitoring systems. Physiological measurements in a real-world environment are unlikely to be perfectly stable. Short but sharp anomalies do not require actual clinical events; naïve systems may trigger them. False alerts can also be excessive, thereby overloading the healthcare personnel and diminishing confidence in automated monitoring systems.

To counter this problem, the suggested framework incorporates a smoothing-based improvement mechanism applied to the machine learning model's output probabilities. Exponential smoothing methods help stabilise predictions over time, so alerts are generated only when abnormal conditions persist. This method will severely minimise false positives at the expense of sensitivity to actual deterioration events. The Sentinel Life Jacket is a piece of architecture divided into five functional layers: Sensing, embedded processing, communication, intelligence, and alerting. Biomedical sensors record physiological signals in the sensing layer [14]. The processing layer was integrated and is based on the ESP32 microcontroller; it cooperates with it. The communication layer transmits additional encrypted data packets to the Flask server over Wi-Fi, ensuring security. The intelligence layer performs preprocessing, including normalisation and feature extraction, and then proceeds to CatBoost-based classification and smoothing. Lastly, the alerting layer provides real-time visualisation via an online dashboard and sends alerts on high-risk conditions to healthcare personnel. The jacket features an OLED display that allows direct visualisation of vital parameters on the device and keeps it functional even during temporary network interruptions. The growing need for scalable healthcare has led to the creation of the Sentinel Life Jacket. There is a general ward in the hospital with limited ICU capacity and patient-to-nurse ratios [15].

Non-stop bedside electronic patient surveillance for all patients outside the ICU might not be cost-effective. The wearable solution is an effective alternative because it enables mobility, eliminates reliance on fixed equipment, and improves patient comfort. Moreover, timely identification of deterioration could help reduce ICU readmissions, shorten length of stay, and lower overall treatment costs. Technically, the proposed system is an elaborate combination of hardware sensing, wireless communication, machine-learning-based prediction, and stabilisation within a single wearable system. Although there are studies on wearable monitoring and AI-based classification, few have investigated both simultaneously, and those that have analysed fewer studies have provided predictive analytics with output smoothing tailored to real-time hospital applications [17]. The use of smoothing, in addition to CatBoost classification, helps increase resilience in changing environments where signal variability is typical. The system design also comprises data security and patient privacy. Physiological data is very sensitive, and as such, secure communication protocols and controlled access control mechanisms are enforced to provide confidentiality. Its architecture is also scalable and adaptable, enabling it to support future connections to hospital information systems, cloud-based analytics solutions, and electronic medical records.

2. Related Works

The use of continuous health monitoring and early warning systems has received significant attention in recent years, as they can help improve patient safety beyond the intensive care setting [1]. The development of wearable sensing, wireless communication and machine learning technologies has allowed remote physiological monitoring to be more easily and responsively accessed. Nevertheless, despite these technological advances, there are still problems in achieving reliable, real-time prediction, reducing false alarms, and making the technology useful to clinicians in real healthcare environments. Early systems of patient monitoring were primarily concerned with integrating wearable sensors to obtain physiological data. For example, after creating a wearable heart-monitoring system, Zang et al. [30] combined ECG and pulse sensors to record vital signs and transmit them via mobile technology. Though these systems enabled remote data collection, they relied mostly on predetermined threshold-based alert systems. Such fixed thresholds were not always able to capture the complex interdependencies among physiological parameters, resulting in high false-alarm rates and low clinical interpretability [32]. Later studies proposed Internet of Things (IoT)-based health systems to enhance the network and access. Zeshan et al. [27] proposed an IoT-based remote patient monitoring system using Bluetooth Low Energy and cloud storage to enable physicians to access patient data.

On the same note, Jangra and Gupta [21] developed a smart IoT system that monitored patients in real time, with web-based dashboards for data visualisation. Although the proposed architecture mitigated the problem of spatial distance between patients and caregivers, it relied heavily on predefined threshold specifications and could not predict patient-specific physiological patterns. To address these shortcomings, machine learning methods have been widely adopted for predicting clinical risks. The conventional methods used in cardiovascular abnormality screening and risk stratification include support vector machines, k-nearest neighbours, and random forests [23]; [26]. Javeed et al. [31] found that random forest models outperformed statistical models in detecting cardiovascular anomalies. However, traditional machine learning methods tend to be inadequate for handling heterogeneous clinical data and require preprocessing of categorical variables on a scale. Moreover, the models can be overfit unless feature engineering is done [5]. Gradient boosting algorithms have become promising substitutes for structured healthcare data analysis. XGBoost and LightGBM have been used for sepsis prediction and early identification of physiologically deteriorating ICU patients [22]. These techniques have better predictive accuracy, but problems like predictive shift and target leakage, particularly when using categorical features, are still problems when strong encoding measures are not employed.

The solution to these problems is the introduction of CatBoost by Jun et al. [18], which uses ordered boosting and built-in target statistics to handle categorical features [28]. It is especially applicable to healthcare, where it can handle heterogeneous features without much preprocessing. Recent research has shown that CatBoost can be useful for mortality prediction using electronic health records and for detecting adverse events in wearable health systems [19]. These results indicate CatBoost's strong generalisation and reduced overfitting, making it suitable for real-time clinical classification [17]. Although newer predictive modelling methods have been developed, the stability of real-time deployment remains a challenge. Physiological signals captured by wearable watches are highly susceptible to noise and motion artefacts, as well as temporary noise, resulting in inconsistent detection. Alarm fatigue remains one of the most important problems in healthcare settings because false positives make caregivers less responsive and trustworthy. To curb these problems, several research studies have examined methods for smoothing signals and reducing noise. To classify wearable ECG signals, Jerard et al. [33] used moving-average filters to remove transient spikes [29]. On the same note, time-varying vital trends have been estimated using Kalman filtering techniques to obtain robust state predictions [24]. These methods can be used to stabilise the signal, but are not typically implemented in the classification decision layer, as they are typically applied at the signal level. From a systems integration perspective, few studies have integrated wearable sensing, predictive machine learning, a clinician dashboard, and real-time alert systems into a single system.

Motewar et al. [22] proposed a unified IoT-cloud-analytics framework to manage chronic diseases and provide a notification support system for clinicians [20]. Although the system was shown to be end-to-end connected, it used relatively simple predictive models. It did not specifically address temporal smoothing of model outputs to minimise false alarms. Newer papers have also advanced predictive wearable devices through ensemble learning, federated learning, and adaptive smoothing. Ali et al. [1] introduced ensemble-based prediction of heart health using wearable devices. Reddy et al. [3] introduced an ECG- and SpO2-based early warning system based on ensemble learning [2]. In contrast, Borowski et al. [4] specifically focused on reducing false alarms with adaptive smoothing algorithms in a clinical monitoring setting. The contributions focus on the significance of integrating predictive intelligence and time-stability processes into real-world healthcare systems. The suggested Sentinel Life Jacket system is based on these existing studies. It integrates enhanced machine learning, real-time physiological monitoring, and a refining-smoothing decision layer into a single wearable surveillance system. Compared with traditional systems based on thresholds, the proposed approach uses CatBoost to model complex multivariate associations among physiological parameters. Moreover, a special processing system is added during the prediction phase to stabilise temporal results and minimise the false alarm rate. This system has a Flask API as its backend, a real-time clinician dashboard, and automated alert notifications, which would help address the acute gap in the solution for reliable, intelligent, and continuous post-ICU patient monitoring.

3. Algorithm

The intelligent health monitoring system employs a variety of machine learning algorithms. The CatBoost algorithm and its variant with smoothing are chosen because they can manage heterogeneous data, reduce overfitting and improve stability. The workings of the algorithms incorporated in the suggested system are set out in the next subsections.

3.1. CatBoost Classification Algorithm

CatBoost is an ensemble technique. It uses gradient boosting. It performs well with both numerical and categorical features. To tackle the prediction shift issue, it utilises an ordered boosting strategy that reduces overfitting, a problem often associated with ordinary boosting methods. CatBoost builds each decision tree one after another, adjusting various loss functions, such as cross-entropy, to correct the predecessor’s mistakes. Algorithm Steps, first input data set. Give the training dataset:

$$D = \{ (x_i, y_i) \} \quad (1)$$

Here, y_i refers to the classification labels, and x_i refers to the feature vectors. D is the training data of the supervised learning process. A single case in the dataset comprises a set of features x_i, including measurements of physiological parameters such as heart rate, SpO2, body temperature, respiratory rate, and ECG-related values, as well as the label y_i. The designation refers to the patient's health status, which is mostly Normal or High Risk. This systematic association helps the model to gain insights into the correlation between clinical outcomes and physiological measurements. Before training the models, they undergo preprocessing to ensure quality and consistency. This involves handling missing data, removing noise, and, as necessary, standardising features. Labelled data enables the CatBoost algorithm to learn patterns and relationships among various health indicators repeatedly. A properly prepared dataset has a significant positive impact on the model's capacity to generalise and correctly predict patient risk in real-world deployment scenarios:

- **Preparation:** Fill missing values, minimise noise, and encode categorical features. In this case, the inbuilt ordered target statistics of CatBoost are utilised to prepare the data.

In the preparation phase, CatBoost performs necessary preprocessing tasks to maintain data quality and model reliability. The algorithm encodes the categorical features sequentially using its in-built ordered target statistics to avoid target leakage and reduce bias. This has the advantage of eliminating the need for external encoding strategies such as one-hot encoding, which can be very high-dimensional and complex. Besides, missing data is handled systematically, and small discrepancies are reduced. These preprocessing features enable CatBoost to handle heterogeneous healthcare data. Consequently, the model will be more robust and able to learn meaningful patterns of actual physiological measurements of the world:

- **Configuration:** Specify the model's learning rate, depth, and number of iterations.

At this phase, the core hyperparameters of the CatBoost model are set, and the model is then trained. The learning rate, which governs the input to each additional tree; the tree depth, which dictates the model's complexity; and the boosting iteration, which affects the overall predictive power, are considered important parameters. The choice of these parameters is important for ensuring a balance between accuracy and generalisation. An adequately adjusted setting would help avoid fitting and ensure the model replicates nonlinear associations among physiological characteristics. This action directly affects the system's stability and predictive behaviour. Boosting by order:

- Look for the intended target statistics in sequence for each iteration t.
- Build a symmetric decision tree.
- Determine the gradient of loss.
- Use the newly created tree to update the ensemble.
- Prognosis: The results of the trees are combined with the weights to produce the final classification. CatBoost will perform better on your data. In addition, it is less likely to overfit and leak than conventional boosting models.

During the forecasting phase, the performance of all the constructed trees is combined by summation to yield the final prediction score. A combination of this output is the model's probability estimate of the patient's health status. A point at which the condition is considered either Normal or High Risk is then used.

3.2. Smoothing-Based Enhancement

Although the CatBoost results are highly reliable and discriminative, slight variation can still occur due to temporary sensor noise, motion artefact, or temporary physiological changes. Even minor prediction oscillations in continuous health monitoring settings (particularly among post-ICU patients) may lead to uneven risk classification. To overcome this weakness, a smoothing mechanism is added as the final output stage in the proposed framework. This step aims to add time-invariance to the prediction stream and ensure that classification choices are not overly affected by short-term oscillations. The smoothing strategy is a stabilisation layer to the raw probabilistic results of the CatBoost classifier. The smoothing is achieved through a weighted aggregation mechanism based on the exponential moving average, assigning a controlled weight to the most recent predictions while preserving historical trends. The arrangement of the forecasted probabilities can be denoted as:

$$P=\{p1,p2,p3,\ldots.pn\} \tag{2}$$

Apply Smoothing Function. Compute the smoothed prediction Sn using:

$$Sn = \alpha pn + (1-\alpha)S\, n-1 \tag{3}$$

Using where α is the coefficient of smoothness:

$$(0 < \alpha < 1) \tag{4}$$

3.2.1. Threshold Decision

The balance between responsiveness and stability is determined by a parameter, α. An increase in alpha makes it more sensitive to recent changes, whereas a decrease in alpha makes it smoother, focusing on historical trends and producing a stabilised output. Sn, a decision mechanism based on the threshold is used. If Sn >= T, the case is considered abnormal; otherwise, it is normal. By combining this temporal filtering, the error rate of false positives is minimised, and sudden classification switches are reduced. This will improve the models' robustness, alerting stability, and reliability in real-time healthcare monitoring applications. As a result, the smoothing mechanism enhances the practical usefulness of the proposed intelligent monitoring framework in clinical settings, where the consistency and reliability of decision support are essential.

3.3. Importance of Smoothing Technique

Patients who have been discharged from the ICU are usually characterised by unstable physiological readings because of their debilitated physical states, constant effects of treatment, or slow recovery processes. In these instances, sensors can be erratic even in the absence of an actual clinical emergency. In the absence of stabilisation, the prediction model can oscillate between risk categories, resulting in inconsistent outputs. The smoothing mechanism provides a temporal filter that mutes short-term changes while maintaining long-term trends. The system is more reliable and clinically significant by eliminating small-range fluctuations in the predicted probabilities. True anomalies (including long-lasting oxygen desaturation or continuing tachycardia) can still be detected, whereas the noise is smoothed out. CatBoost and smoothing integration thus provides an equal mix of High predictive accuracy, high generalisation ability, Temporal stability, Reduced alarm fatigue, and improved clinical reliability.

4. Embedded System

The Sentinel Life Jacket is a wearable monitoring device that continuously measures heart rate, SpO_2, body temperature, and respiratory rate. The system sends recorded data to the monitoring server using wireless technology. ML model decisions help find abnormal trends that may mean clinical decline.

4.1. Design

The Sentinel Life Jacket's overall design focuses on continuous generation, processing, and interpretation of vital signs using a compact IoT architecture. The system input, comprising various biomedical sensors such as heart rate, SpO_2, respiration, and temperature, is shown in the block diagram. In real-time, the sensors send physiological data to the ESP32 microcontroller. The processed data is sent to a Python machine learning model that uses the pre-trained CatBoost classifier to predict risk levels. The ESP32 can connect to an OLED display for displaying real-time vital readings. Also, a notification module is activated whenever the system detects anomalous or high-risk events, notifying medical personnel. This easy-to-use, compact design delivers continuous, low-power consumption smart monitoring of the patient’s condition. The jacket must be easy to wear and balanced, so it does not cause discomfort or limit the patient's movement. The wearable system will utilise long-lasting batteries to enable active monitoring of post-ICU patients for extended periods. A longer battery life will reduce the need for frequent recharging, which, in turn, minimises interruptions in monitoring and enhances reliability in both clinical and home-care environments. This guarantees uninterrupted data collection and prompt alert generation, which are important for patient safety. The system consists of the following:

- **Biomedical Sensors:** To keep track of heart rate, oxygen saturation, temperature, and movement.
- **Microcontroller:** Transmits real-time data.
- **CatBoost ML Model:** Classifies patient condition as normal or critical.
- **Smoothing Layer:** Removes noise and fluctuations in vital signals.
- **Alerting Module:** Sends messages or an application-based alert to a clinician.

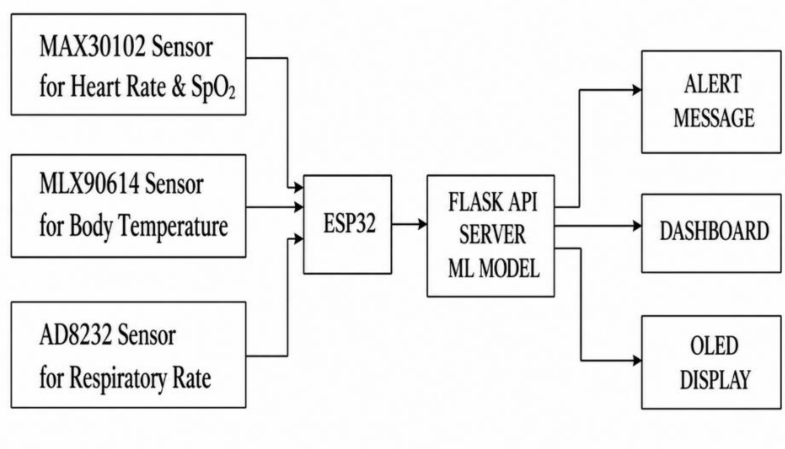

Figure 1: Functional block diagram of the Sentinel Life Jacket Integrated ML-Based Patient Observation System

The jacket has all the physiological sensors built in, and therefore, vital signs can be continuously monitored without any external attachments. The sensor's positioning is stable, and it does not produce significant signal noise during motion, allowing continuous data recording. The sensors integrated into the jacket also ensure that patients and caregivers can use it easily. The block diagram in Figure 1 shows the general working architecture of the Sentinel Life Jacket system. The system's input comprises biomedical sensors. The sensor is the MAX30102, which measures heart rate and SpO2; the sensor is MLX90614, which measures body temperature; and the sensor is the AD8232, which measures respiratory-related signals (and ECG, when combined with it). These sensors continuously monitor the patient's physiological information. The collected signals are then transmitted to the ESP32 microcontroller, which serves as the central processing and communication unit. The ESP32 reads the sensor values, performs initial processing, and the data is ready for transmission. Once the data has been collected, the ESP32 transmits the physiological variables wirelessly to the Flask API server, where the machine learning model (CatBoost) is used to analyse the data to identify the state of patient condition as either unproblematic or high risk. Depending on the prediction results, the system produces the correct outputs. If an abnormal condition is detected, an alert message is issued. Prediction outcomes and processed data are also shown on the real-time dashboard for doctors, as well as on the OLED display for quick access to local data. Full flow guarantees continuous observation, smart risk prediction, and prompt notification in emergencies.

4.2. Implementation

The proposed patient monitoring system operates systematically, from the Alarm Generation Module through Central Monitoring and Timely Notification Delivery [8]. The workflow completes tasks quickly with minimal delay. This system is reliable enough for continuous monitoring in post-ICU care, senior citizen care, and remote medical monitoring [6]; [7].

4.2.1. Data Acquisition Phase

At this stage, the wearable device is implanted with all necessary biomedical sensors, which acquire body parameters such as heart rate, SpO_2, temperature, and body movement. The microcontroller works with raw signals. Next, it performs basic filtering. Finally, it sends the signals as data packets to the Flask API, which acts as a server.

4.2.2. Preprocessing and Feature Engineering

Once the sensor data is collected, the system filters for lie removal, normalises the data, and aggregates. The distinctive characteristics of a patient are conveyed over time through data. These feature vectors are used to input the classification model. When needed, strategies for handling missing values and removing noise are utilised.

4.2.3. Classification and Decision Layer

The CatBoost classifier uses the engineered features to predict the patient's condition as normal, warning, or critical. When the smoothing Layer is added, the classifier's outputs are smoothed before a final decision is made (Figure 2).

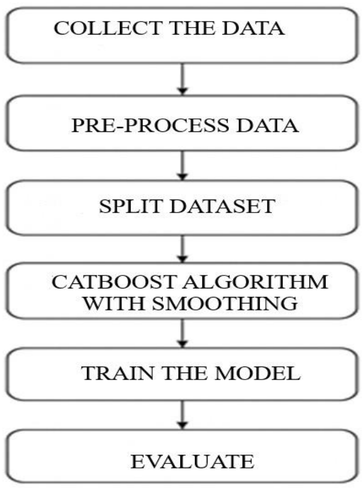

Figure 2: Steps to train an ML model

As a result, researchers avoid common misclassification due to unexpected bodily changes, such as sensor artefacts. The machine learning model for the Sentinel Life Jacket used the entire pipeline. The process begins with collecting physiological data; vital parameters such as heart rate, oxygen saturation, temperature, and respiratory rate are collected from several people.

After the raw data is acquired, noise is removed, artefacts are filtered, values are normalised, and missing entries are imputed, making the dataset clean for machine learning analysis. Partitioning the Preprocessed Dataset into Training and Testing Sets for Model Efficiency Evaluation. In the next process, the Catboost classification algorithm was applied. This was done because of its ability to handle heterogeneous biomedical features. Moreover, Catboost avoids overfitting by ordered boosting [9]; [10]. The model is continuously trained to recognise patterns of normal and abnormal physiological states. The last step of the model validation is the evaluation stage. In this stage, the model's performance is evaluated using metrics such as accuracy, precision, recall, and F1 score [11]. This orderly progression helps build a solid, dependable prediction model that serves as the intelligence centre for the Sentinel Life Jacket's real-time risk classification system [12].

4.2.4. Alert Triggering Mechanism

The FLASK API acts as a server that recognises a critical state, and the alerting module gets triggered. The system instantly sends notifications to the doctor, medical personnel, or registered emergency contacts. These alerts may be delivered through. Mobile application notifications and dashboard prompts for health operators. It ensures quick action and fast clinical response. In clinical practice, alerts must be generated promptly to ensure patient safety. The system can identify abnormal physiological trends and provide alerts quickly, enabling quick clinical intervention. Early notification of deterioration would enable timely intervention and reduce disaster outcomes in post-ICU patients.

4.2.5. Continuous Monitoring Loop

Basically, the suggested system operates on a continuous monitoring cycle in which physiological information is captured, processed, and analysed at regular time intervals. Every monitoring cycle, the integrated biomedical modules yield new sensor values, which are preprocessed to eliminate noise and discrepancies, and converted to informative feature vectors used to make model inferences. The trained CatBoost classification model is then run to produce a probability score indicating a patient's risk status. The smoothing mechanism then stabilises the predictive output and determines the final decision on whether to generate alerts [13]; [16]. This is an iterative process, structured so that predictions do not occur in a vacuum but rather as part of a dynamic temporal evaluation. The feedback process is adaptive and continuous. With each new physiological reading integrated into the system, the prediction output is recalculated and refined on the fly [14]; [15]. This enables the model to exhibit a gradual deterioration trend rather than only instant threshold violations. The combination of smoothing helps minimise sudden changes in classification, reducing the likelihood of false positives and unnecessary alarms. This decrease in alarm fatigue is especially crucial in post-ICU and high-dependency monitoring settings, where too many alerts can saturate medical staff.

4.2.6. Data Security and Privacy

Clinical and physiological information is sensitive in nature as it involves personally identifiable information and important health parameters that cannot be exposed to unauthorised access and abuse. Thus, enhancing data security and privacy is a fundamental requirement for the proposed Sentinel Life Jacket. The architecture will facilitate safe acquisition, transmission, processing, and storage of patient data across all system elements, including wearable devices, wireless communication units, and a Flask-based Server at the backend. To protect information during transfer, an encryption mechanism is used to prevent unauthorised access and interference. The communication protocols between the ESP32 device and the backend Server are secured, ensuring that physiological data are encrypted and their integrity is guaranteed. Also, the monitoring dashboard and patient records are authenticated and authorised using role-based mechanisms. Patient information can be accessed and amended solely by certified medical practitioners, thereby reducing the risk of breaches and unwarranted leakage. At the end of the storage, patient records are stored in encrypted databases with controlled access policies and frequent system checks. Practices regarding data handling comply with accepted standards of medical data security and medical ethics to uphold patient confidentiality and comply with regulations. The proposed system improves trust and guarantees that patient privacy is preserved, even in real-time remote monitoring settings, by incorporating components such as encryption, secure communication, controlled access, and unified data protection practices.

5. Results Analysis

To build an accurate and reliable health-risk prediction system, the machine learning model is trained on a physiological dataset comprising heart rate, SpO_2, body temperature, respiration rate, systolic and diastolic blood pressure, age, gender, height, and weight from Kaggle. The dataset consists of 200020 patient records, each representing an individual patient occurrence at a particular clinical observation point. The class distribution is binary (Low Risk and High Risk) and rather equal, as shown in the dataset distribution plot. An 80:20 stratified train-test split was used to divide the data set. Figure 3 indicates the distribution of instances across the two risk groups in the dataset: High risk and Low risk.

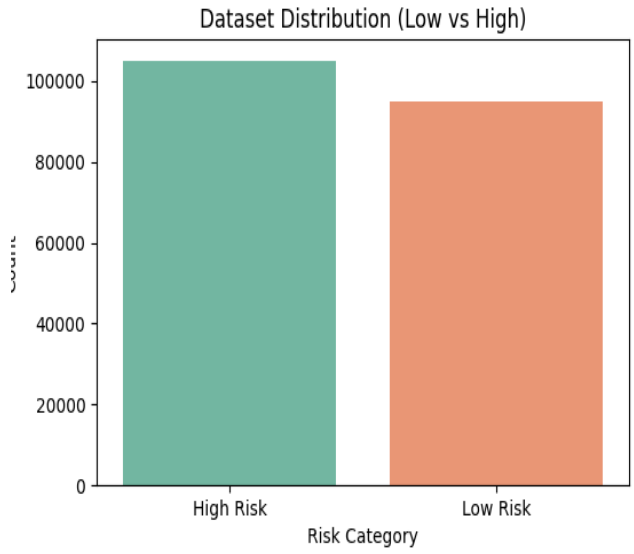

Figure 3: Class distribution of the dataset

The bar chart-based representation shows that the dataset is relatively balanced; however, the high-risk samples are slightly more numerous than the low-risk samples. This type of distribution is beneficial in supervised learning because it prevents the model from being biased towards a dominant class and enhances generalisation. A balanced dataset is especially significant for healthcare risk prediction, as class imbalance can lead to low detection of clinically significant cases. The almost homogeneous distribution in Figure 3 enables stable model training and increases the validity of performance measures such as accuracy, precision, recall, and AUC. In turn, the dataset structure enhances the robustness and impartiality of the proposed CatBoost-based classification model.

Table 1: Model classification results

No.	Algorithm used	Accuracy
1	Random Forest	66.08
2	CatBoost Model	75.68
3	CatBoost with Smoothing	99.66

Table 1 shows the accuracy of three machine-learning models: Random Forest, CatBoost, and CatBoost with smoothing. The Random Forest indicates that the low accuracy suggests this dataset has complex categorical patterns. Random Forest was evidently too limited to capture them. It is not suitable for high-cardinality categorical features without thorough preprocessing (Table 2).

Table 2: Model accuracy for catboost with smoothing

Metric	Value
Model Accuracy	99.66

The standard CatBoost classifier was found to improve accuracy to 75.68%, demonstrating its strong ability to handle categorical variables via ordered boosting and target encoding. The approximately 9.6% improvement validates CatBoost's internal ability to reduce overfitting and better manage category sparseness than Random Forest. The accuracy rate improved to 99.66% by smoothing out the categorical target statistics. The results, which are very close to the perfect case, indicate that smoothing reduced noise, stabilised category encoding low-frequency classes, and reduced variance during training. The confusion graph shows very low false-positive and false-negative rates, whereas the prediction probability distribution shows distinct classes. These were combined with stability in test-set performance, suggesting that the high accuracy can be explained by high feature discriminability rather than memorisation or leakage. Table 3 indicates that model performance was evaluated on a separate held-out test set, not used for training or hyperparameter optimisation. This evaluation plan is an effective way to assess the model's generalisability to unknown patient data. The high overall accuracy, precision, recall, F1-score, and ROC-AUC findings indicate the model's high generalizability across the data distribution. Figure 5 shows the Receiver Operating Characteristic (ROC) curve and the area under the curve (AUC), which provides a holistic, threshold-free assessment of the model's classification performance. A ROC curve is a graph that shows the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) at different decision thresholds.

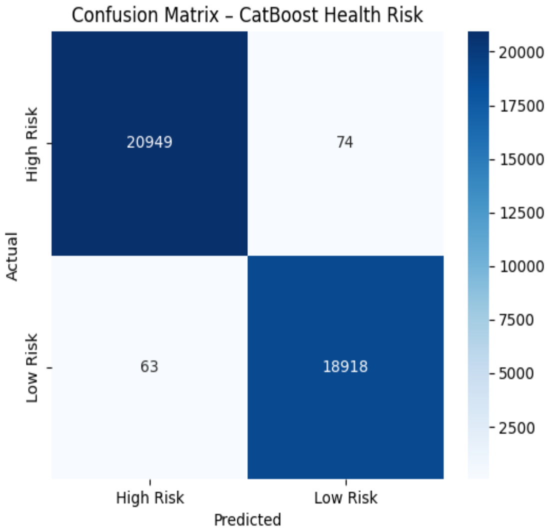

Figure 4: Confusion matrix of the trained model

Through curve analysis, one can determine the model's effectiveness in separating low- and high-risk patients at different sensitivity levels. The CatBoost model achieved an AUC of nearly 1.0, which is quite good for discriminative ability. A value of AUC near 1 indicates that the model can distinguish the two classes with minimal ambiguity in the predicted probabilities. This is practically interpreted to imply that high-risk patients always have a higher probability than low-risk patients.

Table 3: Model Performance

Parameter	Value
Precision	99.61%
Recall	99.67%
F1 score	99.64%
ROC AUC	1.0

This performance indicates the CatBoost algorithm's strong learning ability to capture intricate, nonlinear relationships among multiple physiological parameters. A high AUC also indicates that the model has good predictive performance, regardless of the classification threshold a researcher uses.

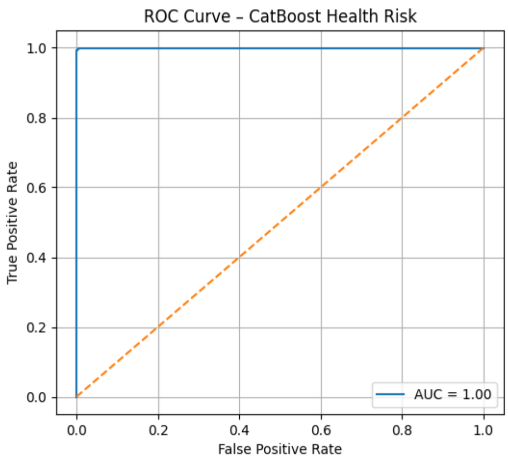

Figure 5: ROC curve of the trained model

This is especially significant in medical applications where the decision thresholds can be set based on clinical priorities. As a case in point, in monitoring critical care patients, increased sensitivity can be desired because it ensures that worsening conditions are detected early, even at the expense of a few more false alarms. The ROC analysis will demonstrate that the proposed model is robust across different threshold settings. In general, the ROC and AUC analyses confirm the usefulness of the suggested classification system. The AUC score of 0.999 indicates that the CatBoost-based system is a reliable tool for risk stratification, supporting its selection as suitable for real-time post-ICU patient monitoring and early clinical intervention. The real-time prediction interface runs on the Visual Studio Python application and is shown in Figure 4. The user inputs essential parameters such as heart rate, respiratory rate, oxygen levels, and body temperature. The model assigns a health risk category based on feature values. In this case, the system classifies the patient as high risk. Another warning that does not affect the model's workings or output is a Data Conversion Warning from scikit-learn. Researchers can use this model in real time to make clinical decisions, as shown in Figure 6.

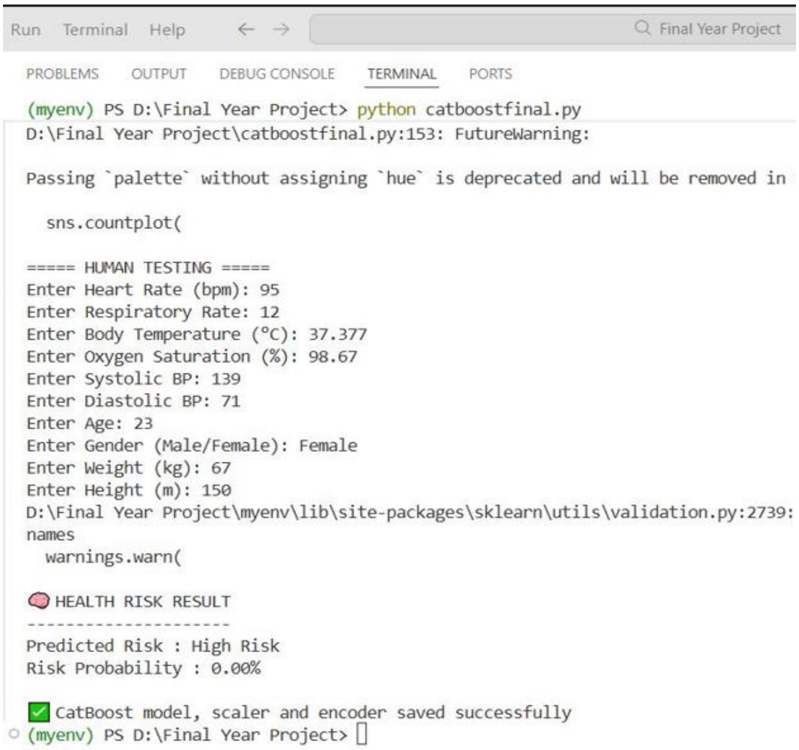

Figure 6: Result of evaluation

Once the CatBoost-based classification model has been trained and tested, it must be deployed to a real-time operational setting. In its clinical implementation, the predictive model should operate around the clock and respond immediately to incoming physiological data. To do so, the trained model is incorporated into a Flask-based web server that serves as the backend prediction engine. The web-based monitoring dashboard is built with Flask, a lightweight Python web framework, which connects the wearable hardware module to the dashboard. The trained CatBoost model is saved as a serializable model that can be loaded in the Flask environment at runtime. This would give it an advantage in making real-time predictions if new patient information becomes available. Since the ESP32 transmits physiological parameters, the Flask API does the following operations:

- Receives sensor data in real time, in a structured format.
- Checks and processes for the received parameters.
- Parameters of the features based on the trained model demands.
- Python implementation of the CatBoost prediction model.
- Enforces a smoothing mechanism on the output.
- Produces the ultimate classification (Normal or High Risk).
- Forwards the data to the doctor monitor.
- Raise alert messages for abnormal conditions.

The doctor dashboard is the graphical user interface of constant patient monitoring. It is lint-free with the Flask backend and is automatically updated whenever new predictions are made. The dashboard will offer concise, relevant, and clinical information to the healthcare personnel. The interface shows the following physiological parameters:

- Heart Rate (beats per minute).
- Percentages of Saturation with Oxygen (SpO 2).
- Body Temperature (°C).
- Respiratory rate (puffs per minute).
- ECG waveform visualisation.

Prediction of the health condition using machine learning. The ECG is displayed as a waveform, allowing cardiac rhythm patterns to be visually evaluated. Numerical values are presented alongside graphical features to facilitate rapid clinical understanding. It has a colour-coded indicator of health status that may be recognised instantly:

- Normal conditions are denoted by greenery.
- Red represents high-risk conditions.

The design allows the doctor to quickly evaluate the patient's condition and take appropriate action without manually analysing raw sensor data—an automated Alert and Notification Mechanism. The automatic alert system will notify the user when the system is ineffective or when it is rebooted with unknown data. The Flask backend includes an automated notification module to ensure prompt intervention when a problem arises at an early stage. If the smooth prediction probability exceeds a specified limit, the system recognises the condition as abnormal. On identification of a High-Risk state:

- The health status indicator is updated with the dashboard:
    - The abnormal parameter is emphasised.
    - A message is dispatched to the duty physician or nursing personnel.

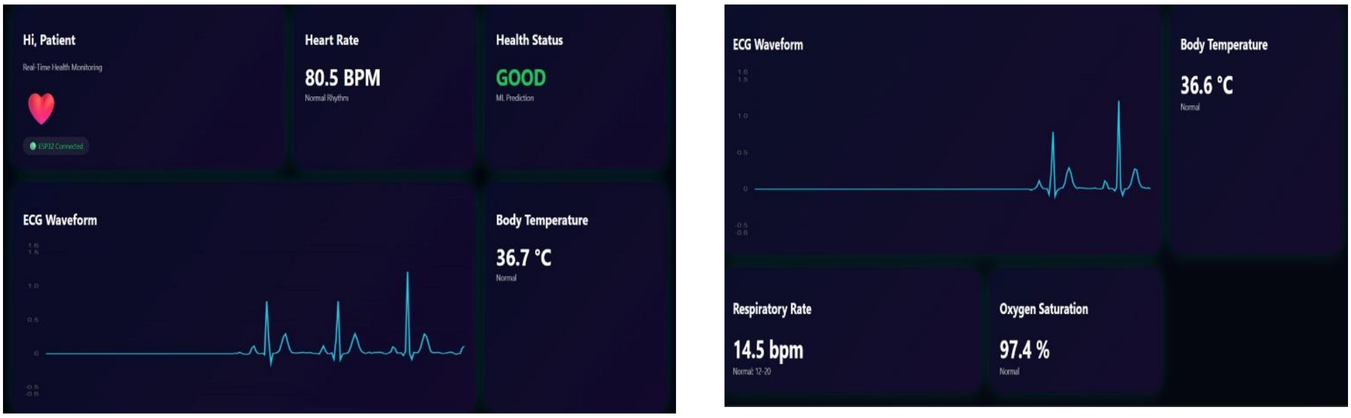

Figure 7: Dashboard for a doctor

Such a proactive warning system saves significant time in response compared to periodic manual checks. Also, by applying smoothing followed by threshold comparison, false alarms caused by transient signal variations are reduced. This minimises alarm fatigue and enhances clinical trust in the system. This architecture guarantees low latency, high reliability, and the availability of predictions at all times. The system is modular and scalable, with the hardware layer decoupled from the machine learning layer. In Figure 7, the dashboard provides real-time doctor data on vital parameters, including heart rate, ECG waveform, body temperature, respiratory rate, and SpO_2. The interface also includes health status prediction (Normal/High Risk), based on machine learning, enabling fast clinical evaluation and early intervention. The hardware prototype will be an ESP32 microcontroller with several biomedical sensors. The main processing and communication chip of the wearable system is the ESP32. The hardware materials consist of:

- MAX30102 sensor for heart rate and oxygen saturation.
- MLX90614 sensor for non-contact body temperature.
- AD8232 ECG signal acquisition module.
- Sensor on the respiratory rate.

The ESP32 will receive the analogue and digital signals from these sensors, condition them as needed, and assemble structured data packets for transmission. The processed data is then sent wirelessly over Wi-Fi to the Flask server. Physical implementation enables continuous monitoring of the patient and their movement. The compact design allows it to be incorporated into wearable designs, such as the suggested Sentinel Life Jacket. The full hardware prototype of the proposed Sentinel Life Jacket system is depicted in Figure 8. The ESP32 microcontroller is at the heart of the architecture, serving as the central processing and communication unit.

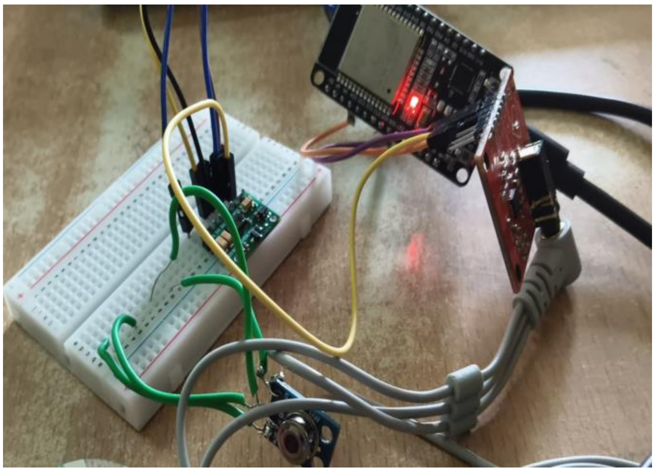

Figure 8: Hardware setup

It communicates with several biomedical sensors, including the MAX30102 heart rate and SpO2 sensor, the MLX90614 non-contact body temperature sensor, and the AD8232 ECG signal sensor. These sensors are well placed to record accurate physiological signals simultaneously, without taking up much space and being comfortable to wear. The ESP32 receives signals from the analogue and digital modules, respectively, preprocesses them in the initial stage, and prepares the data for transmission. The physical setup demonstrates real-time data collection and flawless wireless communication enabled by the built-in Wi-Fi confinement on the ESP32. The perceived physiological parameters are sent to the Flask-based Server, where further processing and machine-learning-based risk classification are performed. This design enables continuous remote monitoring and real-time abnormality detection. The small size of the sensor unit, the microcontroller, and the wireless communication chip is intended to meet low-power requirements, ensure portability, and enable continuous patient monitoring after ICU treatment and in emergency cases.

6. Conclusion

In the current paper, researchers have described the Sentinel Life Jacket. This intelligent wearable health-monitoring device enables us to provide round-the-clock physiological surveillance and real-time alerts for patients at risk during emergencies, after leaving the ICU. The suggested system brings together several biomedical sensors, including heart rate and SpO2 (MAX30102), body temperature (MLX90614), respiratory movement detection, and ECG (AD8232), into a small, wearable platform. These sensors are connected to an ESP32 microcontroller, which acquires and preprocesses data, then transmits it wirelessly to a Flask backend server for further processing. The mobility of sensing, computing, and communication will guarantee continuous observation and the dependability of the data flow in a real-time clinical setting. In contrast to traditional threshold-based monitoring systems, which use fixed alarm limits, the proposed framework will employ a CatBoost-based machine learning classifier to process multivariate physiological data. The model will improve risk-stratification precision and enable early detection of potential clinical deterioration by capturing complex, nonlinear relationships among key parameters.

Moreover, a smoothing process is applied at the prediction level to ensure temporal consistency and minimise variation in classification results. This strategy significantly reduces false alarms and improves system stability and reliability in real-world healthcare settings, where noisy sensor readings and short-lived fluctuations are common. The prototype developed demonstrates that small biomedical sensors, together with small wireless communication sub-units, can be used to create a powerful, scalable, and easy-to-use continuous monitoring system. The dashboard interface allows healthcare professionals to access live vital signs and predictive risk data, and to monitor abnormal conditions indicated by automated alerts. Truly, such an organised visualisation and notification system facilitates prompt clinical intervention and informed decision-making. The system's general architecture eliminates the disconnect between intensive care monitoring and general ward surveillance, providing a cost-efficient, intelligent architecture that improves patient safety, enables remote monitoring, and enhances the efficiency of healthcare services.

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Ethics and Consent Statement: Ethical guidelines were followed, informed consent was obtained from all participants, and confidentiality and privacy were maintained throughout the study.

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