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Yurii MYROSHNYK[1], Oleksandr LESHCHENKO[2]

[1] ***AVI-SPL, Inc., Tampa, USA***
[2] ***National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine***

DEVELOPMENT OF AN AUTONOMOUS SYSTEM FOR IDENTIFICATION AND PREDICTIVE MODELING OF THE PHYSIOLOGICAL STATE OF INDIVIDUALS AT RISK

The article presents the development of a local autonomous system for monitoring and predicting critical physiological states in at-risk-individuals. The system is intended for persons with special needs who live independently or reside in medical care facilities. ***The objective of this work*** *is to develop and substantiate a hybrid model for the real-time assessment and short-term prediction of a person's critical physiological condition. To ensure such an operational mode, the system functions without reliance on cloud services or external infrastructure.* ***The main tasks*** *addressed include the design of a multisensor architecture based on wearable sensors (MAX30102, MPU6050, GY-906), stationary mmWave radars, and a local Home Assistant server. Mathematical models for risk assessment were developed and investigated, including the instantaneous index A(t), the predictive index P(t), and a recurrent LSTM-based model. The* ***methods*** *employed comprise analytical and computational approaches (normalized nonlinear aggregation of deviations, DTW-based comparison with crisis prototypes, Isolation Forest, and k-NN regression for time-to-event estimation), computational–experimental methods (training and validation of an LSTM model on the PhysioNet BOLD dataset), and hardware–software implementation (ESP32 + Home Assistant + InfluxDB/MySQL). The following* ***results*** *were obtained. An instantaneous alarm index A(t) with clinically justified weights and a nonlinear sensitivity function was proposed. An integral predictive index P(t) was developed, incorporating trajectory similarity to crisis episodes, anomaly detection, and the estimated time to event. A dual-channel LSTM model was implemented and tested (ROC–AUC = 0.6956 on the BOLD dataset), enabling the detection of slow degradation trends.* ***Conclusions****. The scientific novelty of the obtained results lies in the proposed autonomous hybrid platform for immediate response and short-term prediction over a 10–30 min horizon, which ensures privacy preservation through the use of mmWave radars instead of video cameras. The models A(t), P(t), and the LSTM approach were further developed and shown to complement each other, enhancing sensitivity to pre-crisis states. This enables the creation of a stable autonomous system, which is particularly important for regions with unreliable infrastructure.*

Keywords*: health monitoring of individuals with special needs; autonomous local system; wearable sensors; mmWave radar; instantaneous risk index; predictive index; LSTM; Home Assistant; early detection of critical conditions.*

Introduction

1. Relevance of the Problem

In the context of the prolonged Russian aggression against Ukraine and, as a consequence, the emergence of a large number of individuals who require continuous monitoring of critical physiological states due to their inclusion in risk groups-particularly servicemen of the Ukrainian Air Force who have been affected in combat zones-the task of developing a specialized system for monitoring and predicting critical physiological conditions becomes especially relevant. This motivates the development of the Care Alarm System (CAS).

Another important issue that currently requires public attention is population aging. This represents one of the key demographic processes of modern society and raises serious concerns. The United Nations reports that the number of people aged over 60 is steadily increasing; according to projections, this figure will exceed two billion by the middle of the 21st century [1]. With advancing age, the risk of developing critical physiological conditions increases. Such conditions include falls [2], respiratory disorders, and fluctuations in blood pressure or cardiac rhythm. The effectiveness of intervention in these cases largely depends on the speed of response.

Even a short delay in providing assistance may lead to severe complications. This problem becomes particularly significant because a large proportion of elderly individuals and people with disabilities live independently, often in regions with limited access to medical care or in areas affected by armed conflict. Under such conditions, shortages of medical personnel and caregivers are common, communication infrastructure is frequently disrupted, and access to emergency services is hindered [3-5]. Reports from humanitarian organizations indicate that this population group is the most likely to remain without timely assistance during emergency situations [3-6].

At present, a wide range of health monitoring devices is available on the market; however, most of them exhibit substantial limitations. In particular:

– many systems rely on cloud services and require a stable Internet connection;

– a large number of solutions lack functionality for detecting slow physiological changes or for predicting the onset of critical conditions;

– camera-based systems raise well-founded concerns regarding privacy violations.

These shortcomings of existing hardware-software solutions necessitate the development of fully autonomous local systems that:

– do not depend on external servers or Internet connectivity;

– provide real-time data processing and decision-making;

– integrate heterogeneous sensor data (motor activity, physiological parameters, and, in some cases, environmental parameters such as ambient temperature and atmospheric pressure);

– and are capable of predicting the development of a critical situation prior to its occurrence.

The proposed Care Alarm System is specifically aimed at addressing this set of challenges by combining multisensor monitoring with local artificial intelligence–based algorithms for risk assessment and prediction of critical physiological states.

2. Review of Existing Systems

Contemporary solutions for monitoring human health at the consumer level encompass a wide spectrum, ranging from simple alerting devices to complex ecosystems with cloud-based analytics. These solutions can be broadly divided into two categories: commercial products intended for mass users and research systems developed in universities and specialized laboratories.

2.1. Commercial Products

The most widespread commercial devices measure a limited set of parameters. These typically include an accelerometer, occasionally GPS, and more rarely basic physiological indicators. Examples include medical emergency alert buttons such as Bay Alarm Medical and smartwatches from Medical Guardian with fall detection functionality [7]. Such systems are fully dependent on cloud infrastructure, which implies subscription fees, the need for a stable Internet connection, and potential delays in the transmission of emergency alerts. Abrupt movements or body tilts during routine household activities often trigger false alarms, which reduces user trust in these systems.

The Apple Watch is among the most technologically advanced mass-market devices. Owing to its sensors and machine learning algorithms, it is capable of detecting falls and cardiac rhythm abnormalities [8]. Its advantages include deep integration with Apple Health/HealthKit [9] and the availability of an FDA-certified application for electrocardiogram recording [10]. At the same time, it is a closed platform with restricted access to raw sensor data. Interaction with external systems is possible only via HealthKit. Emergency alert functions (SOS, fall notifications) require a stable network or cellular connection, which complicates the use of the device in local autonomous medical systems that do not rely on cloud technologies.

A separate niche is occupied by devices based on millimeter-wave radars, such as the Aqara Presence Sensor FP2 [11] and the Milesight VS373 [12]. These devices accurately detect movement, presence, and prolonged immobility without the use of cameras, which is a significant advantage in terms of privacy. However, their functionality is limited: they do not measure physiological parameters and do not perform prediction, but merely register instances of motion.

2.2. Research Systems

The scientific literature proposes more advanced approaches. For example, the mmFall system [13] employs a 4D millimeter-wave radar and a variational autoencoder to analyze the spatiotemporal structure of human motion. This enables very high fall detection accuracy. Some studies combine mobile sensors within multi-layer architectures based on machine learning, where part of the computation is performed locally (edge computing) and another part on remote servers, as in e-health frameworks [14].

Despite their high technical sophistication, most research prototypes exhibit the same drawbacks as commercial solutions, namely dependence on cloud infrastructure and limited integration of heterogeneous sensors. Only a limited number of proposed solutions attempt to integrate wearable devices, contactless radars, and local computation into a single autonomous system.

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2.3. Conclusion of the Review

The analysis of existing solutions indicates that none of the widely used systems simultaneously satisfies the following requirements:

– multisensor integration of data with different modalities;

– full autonomy (operation without Internet connectivity);

– local prediction and decision-making;

– concurrent analysis of motor and physiological parameters;

– open protocols that enable integration with third-party systems and further system evolution.

The absence of comprehensive autonomous solutions with these capabilities necessitates the development of a new system. Such a system must operate offline, integrate heterogeneous sensor sources, provide immediate response to critical events, and predict the user's condition (Fig. 1).

3. System Architecture

The CAS architecture is designed as a sequence of interrelated modules (Fig. 2), each responsible for a specific stage of the monitoring process. In practical operation, this workflow is relatively straightforward. Sensor data are transmitted to Home Assistant with minimal latency, and the system responds to events immediately as they occur. The CAS architecture follows a multi-layer design that combines wearable devices, contact and contactless sensors, and local signal processing. The individual CAS modules are described in more detail below.

3.1. Wearable Modules

The terminal module is an ESP32-based device that acquires physiological signals from three sensors:

– the MAX30102 for heart rate and SpO_2 measurement,

– the MPU6050 for accelerometer and gyroscope data, and the GY-906 for non-contact body temperature sensing.

The ESP32 transmits the collected measurements to an MQTT broker within the local network. Computational logic on the microcontroller itself is kept to a minimum, which results in very low latency. This is a critical requirement for algorithms that rely on immediate response.

3.2. Stationary Sensor Module

The second component is an mmWave radar module (MR60FDA2 or MR60BHA2). This unit operates independently of the wearable device and provides information on motion, falls, immobility, and other events that cannot always be reliably detected using an accelerometer alone. The radars collect data in a format that does not include images; therefore, user privacy is preserved.

3.3. Local Server Module

The central module of the system is Home Assistant, which simultaneosly performs several functions:

– receiving MQTT messages from all modules;

– normalization and preliminary signal processing;

– storage of time-series data in InfluxDB;

– management of events, incidents, and structured records in MySQL;

– execution of the A(t) and P(t) models;

– generation of input sequences for the LSTM model, with prediction processing also performed locally.

The selection of Home Assistant as the core platform is motivated by its scalability, stability, and ability to operate fully autonomously in the absence of an external Internet connection.

3.4. Alerting Module

In the event of an alarm, the system sends local push notifications and initiates a call to a caregiver via SIP or other local communication tools. If required, an automatic call to emergency services can be triggered. All these functions are implemented without the use of cloud APIs. Even in the complete absence of Internet connectivity, the system remains fully functional.

Owing to this architecture, the CAS operates autonomously while retaining the capability to perform relatively complex data analysis and predictive modeling.

4. Mathematical Model for Immediate Response: the Alarm State Index A(t)

4.1. Basic Definition of A(t)

The instantaneous alarm state index A(t) is introduced for the real-time assessment of the critical explainability of a subject's condition. It aggregates normalized sensor deviations while accounting for clinically motivated weights and incorporating radar-based confirmation of the observed events.

It is defined as a bounded sum of elementary sensor deviations:

$$A(t) = \mathrm{sat}\left(\sum_{i=1}^{N} w_i m_i \phi(z_i(t))\right), \qquad (4.1)$$
$$A(t) \in [0,1],$$

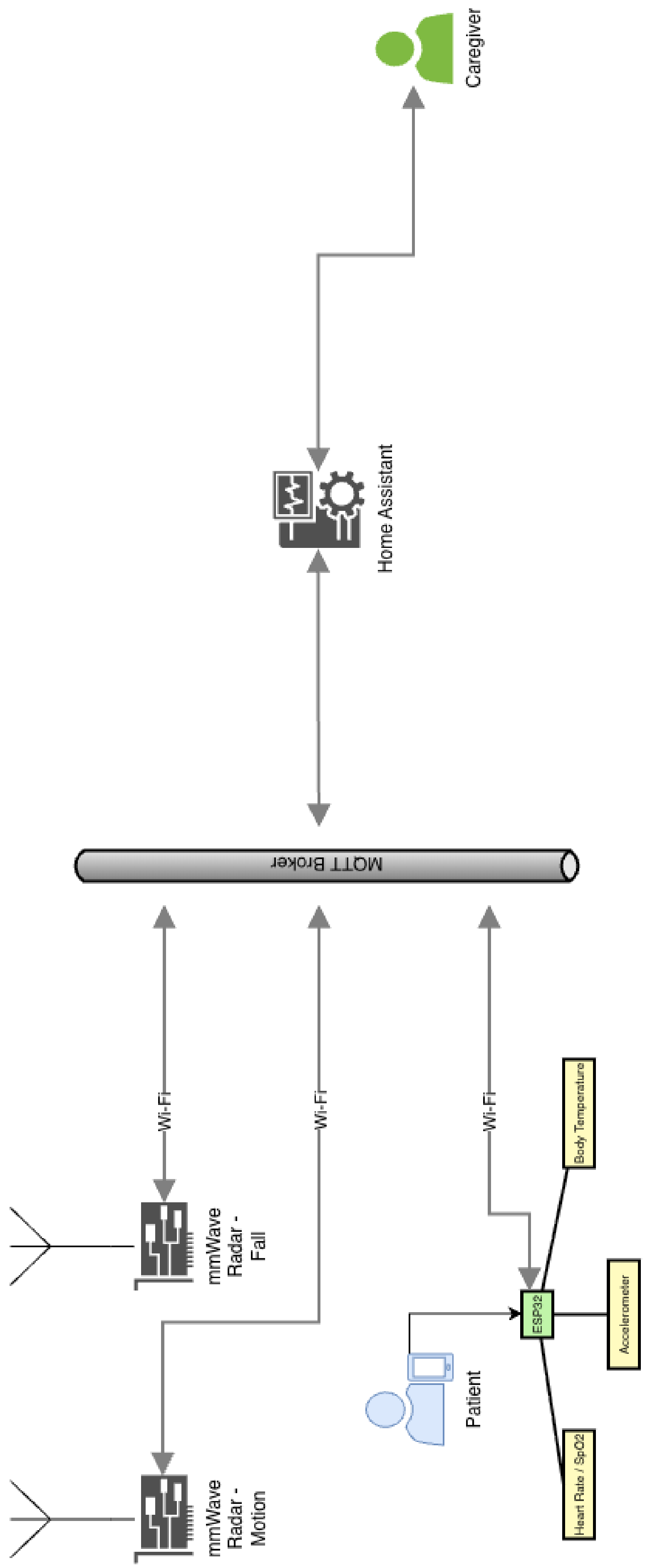

Fig. 1. Care Alarm System

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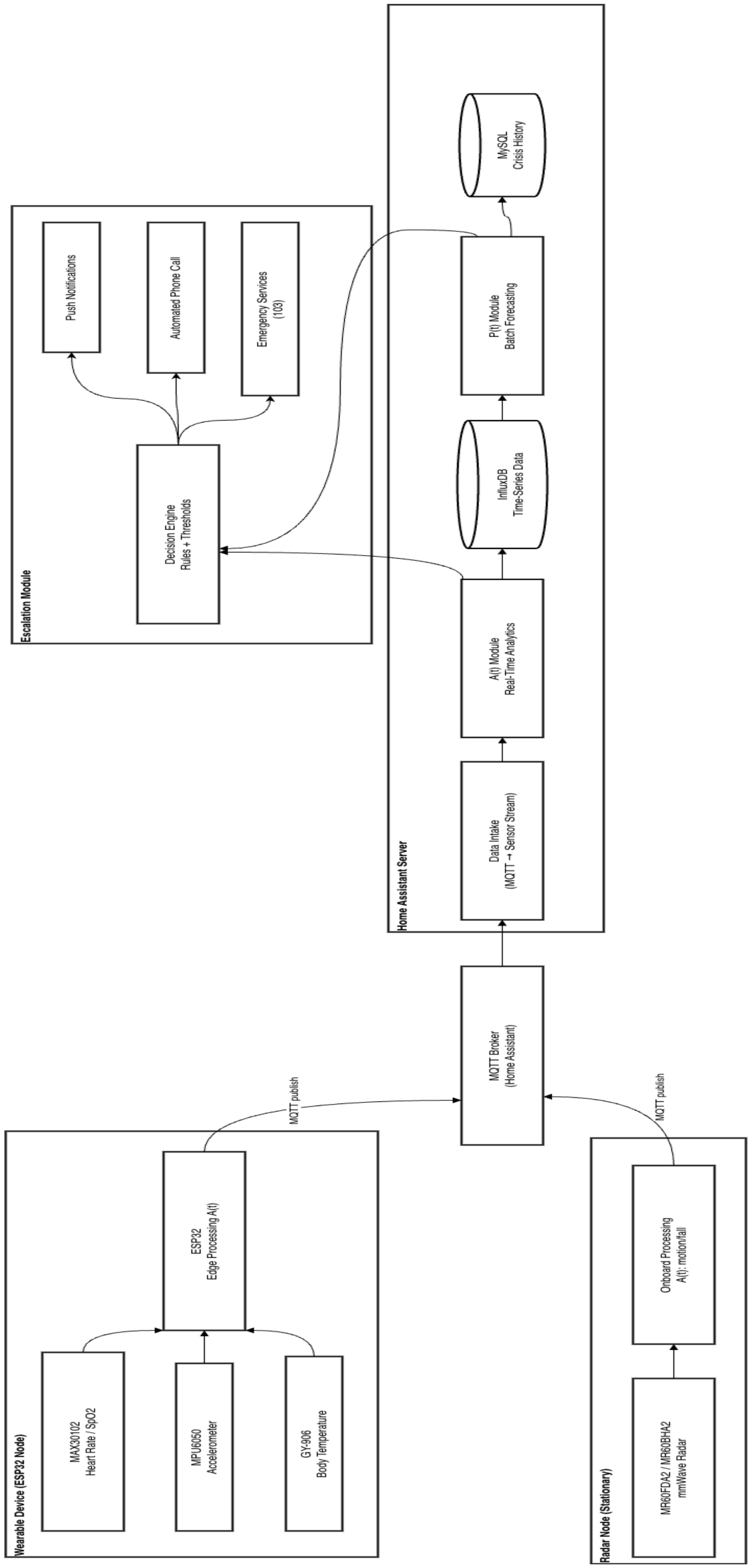

Fig. 2. CAS architecture: edge-based processing of A(t), batch processing of P(t), and a local database

where $i = 1, \dots, N$ denotes the index of a sensor or feature (e.g., heart rate, SpO_2, respiratory rate, temperature, falls, immobility, etc.);

$z_i(t)$ is the modulated z-deviation (z-score) from its baseline value;

$$z_i(t) = \frac{x_i(t) - \mu_i}{\sigma_i}, \quad (4.2)$$

where $x_i(t)$ is denotes the current measured value of the i-th sensor at time t;

μ_i is the mean value;

σ_i is the standard deviation;

$w_i \in [0,1]$ is the clinical weight of the i-th sensor, reflecting its contribution to the overall risk (with the constraint $\sum_i w_i = 1$ for the aggregated score); $m_i(t) \geq 0$ is a contextual multiplier (e.g., signal amplification when a fall is confirmed by radar or when immobility is detected);

$\phi(z)$ is a nonlinear sensitivity function that maps the z-deviation to a dimensionless scale in the interval $[0,1]$;

$sat(\cdot)$ is a saturation operator that enforces a hard bound on the weighted sum of sensor deviations, ensuring that the condition $A(t) \in [0,1]$ is satisfied even in the presence of multiple simultaneous critical deviations. The operator is defined as follows:

$$sat(x) = \begin{cases} 0, & x < 0, \\ x, & 0 \leq x \leq 1, \\ 1, & x > 1. \end{cases} \quad (4.3)$$

4.2. Nonlinear Sensitivity Function $\phi(z)$

The function $\phi(z)$ maps normalized deviations onto a unified sensitivity scale:

$$\phi(z) = \begin{cases} 0, & |z| \leq 0.5, \\ \dfrac{|z| - 0.5}{1.5}, & 0.5 < |z| < 2.0, \\ 1, & |z| \geq 2.0. \end{cases} \quad (4.4)$$

Interpretation:

$|z| \leq 0.5$ corresponds to the range of physiological variability;

$0.5 \leq |z| < 2.0$ indicates gradual risk activation;

$|z| \geq 2.0$ denotes the pathological zone.

4.3. Clinical Weights and Multipliers

The weights of the physiological channels (heart rate, SpO_2, respiratory rate, and temperature) are defined as the absolute values of the correlation between these parameters and in-hospital mortality (in_hospital_mortality) in the BOLD dataset. This approach enables a quantitative assessment of which vital signs are most informative regardingfatal outcomes. For fall events and prolonged immobility, which are not represented in the BOLD dataset, expert clinical assessments are employed, as their critical importance for home monitoring is beyond doubt.

Table. 1 presents the aggregated final values of the weights w_i and the multipliers m_i used in the $A(t)$index.

Verification of the Weight Sum:

$$0.20 + 0.20 + 0.19 + \\ +0.16 + 0.13 + 0.12 = 1.00.$$

An explanation is provided for the mmWave radar + IMU combination. This configuration integrates a millimeter-wave radar sensor with an inertial measurement unit (accelerometer and gyroscope), enabling accurate detection of falls, abrupt posture changes, and prolonged immobility.

For each vital sign $x_i \in \{HR, SpO_2, RR, Temp\}$, the Pearson correlation coefficient r_i with in-hospital mortality is computed as follows:

$$r_i = Corr(x_i, mortality). \quad (4.5)$$

In practical calculations based on the BOLD dataset, the following values were obtained (rounded to three decimal places):

HR: $|r_{HR}| \approx 0.111$,

SpO_2: $|r_{SpO_2}| \approx 0.130$,

RR: $|r_{RR}| \approx 0.156$,

Temp: $|r_{Temp}| \approx 0.104$.

Since the strength of the connectionis of primary importance rather than its direction, the absolute values of the correlations $|r_i|$ are used. A normalization constant is then introduced:

$$R = |r_{HR}| + |r_{SpO_2}| + |r_{RR}| + |r_{Temp}| = 0.111 + \\ + 0.130 + 0.156 + 0.104.$$

The model assumes that the cumulative contribution of physiological parameters to the $A(t)$ index is $W_{phys} = 0.60$. This implies that 60% of the total weight of $A(t)$is attributed to vital signs, while the remaining 40% is reserved for critical motion-related events (falls and immobility), which are not present in the BOLD dataset but are essential in the real-world CAS implementation. Accordingly, the weight of an individual physiological channel is defined as:

$$w_i = W_{phys} \cdot \left(\frac{|r_i|}{R}\right), \quad (4.6) \\ i \in \{HR, SpO^2, RR, Temp\}.$$

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Table 1

Weights w_i and Multipliers m_i for the Components of the $A(t)$ Index

#	Component	Data Source / Sensor	Rationale (BOLD / Expert-Based)	Weight w_i	Multiplier m_i
1	Fall event	mmWave radar + IMU	Falls are not present in the BOLD dataset; however, within the proposed system, a fall represents the most critical instantaneous event	0.20	3.0
2	Immobility	mmWave radar + IMU	Prolonged immobility following a fall or occurring independently (risk of loss of consciousness or death)	0.20	3.0
3	Respiratory rate (RR)	vitals_resp_rate	Highest $\lvert r \rvert$ with in_hospital_mortality among vital signs (~0.16), indicating the strongest physiological predictor	0.186	3.0
4	SpO_2	SpO2	$\lvert r \rvert \approx 0.13$: oxygen desaturation is strongly associated with poor outcomes	0.156	2.0
5	Heart rate(HR)	vitals_heart_rate	$\lvert r \rvert \approx 0.11$: tachycardia is a significant but comparatively weaker predictor	0.133	1.0
6	Body temperature	vitals_tempc	$\lvert r \rvert \approx 0.10$: hypo-/hyperthermia are clinically relevant, but less discriminative than RR and SpO_2 in the BOLD dataset	0.125	1.0

That is, each physiological indicator receives a share of the total weight 0.60 proportional to the strength of its statistical association with mortality. The highest weight is assigned to respiratory rate (RR), which exhibits the largest absolute correlation, followed by SpO_2, then heart rate (HR), with body temperature receiving the lowest weight. The resulting values $w_i = \{0.186, 0.156, 0.133, 0.125\}$ are fully derived from the BOLD dataset.

The events of "fall" and "prolonged immobility" are not represented in the BOLD dataset and therefore cannot be evaluated through correlation with mortality within this database. Nevertheless, in the context of home monitoring of elderly individuals, these events are of critical importance:

– a sudden fall often represents the first indicator of an acute event (e.g., stroke, myocardial infarction, syncope);

– prolonged immobility, whether following a fall or occurring independently, is associated with loss of consciousness and increased risks of pressure ulcers, hypothermia, rhabdomyolysis, and related complications.

Accordingly, the weights for these two components are determined based on expert clinical judgment as follows:

$$w_{fall} = 0.20,\ w_{immobility} = 0.20.$$

Thus, the total weight of all components is given by

$$\sum w_i = 0.60 \text{ (physiological parameters)} + 0.20 \text{ (fall)} + 0.20 \text{ (immobility)} = 1.00,$$

which ensures a normalized interpretation of $A(t)$ within the range $[0,1]$. The weights w_i reflect the average "importance" of each channel, but they do not determine how sharply the $A(t)$ index should increase when a specific parameter exceeds its acceptable limits. To capture this effect, multiplicative factors m_i are introduced to model the clinical acuity of deviations:

$m_{RR} = 3.0$ is respiratory disturbances (respiratory rate) are among the most critical factors;

$m_{SpO_2} = 2.0$ is oxygen desaturation (decreased SpO_2) substantially worsens prognosis;

$m_{HR} = 1.0$, $m_{Temp} = 1.0$ is tachycardia and temperature deviations are important but less specific;

$m_{fall} = 3.0$, $m_{immobility} = 3.0$ is falls and prolonged immobility are treated as potentially fatal events and therefore should maximally amplify $A(t)$.

Intuitively, this means that when RR, SpO_2, or fall/immobility events enter the "red zone," the system should respond much more aggressively than, for example, to an isolated moderate deviation in body temperature.

4.4. Example of A(t) Calculation

Consider a real patient from the PhysioNet BOLD dataset (file bold_dataset.csv), corresponding to the record with unique_subject_id = 89 (row 90 in the file).

For this subject, the instantaneous values of vital signs are available as real sensor measurements (BOLD, unique_subject_id = 89), summarized in Table 2.

Table 2

Instantaneous Values of Vital Signs

Parameter	**Symbol**	**Value $\mathbf{x_i(t)}$**
ЧСС (bpm)	$x_{HR}(t)$	143.0
SpO_2 (%)	$x_{SpO2}(t)$	93.0
Respiratory rate (1/min)	$x_{RR}(t)$	55.0
Temperature (°C)	$x_{Temp}(t)$	36.2

To quantify the deviation from a "normal" state, population-level means and standard deviations computed over the entire BOLD dataset are used for the same columns:

– mean values (from bold_dataset.csv):

$$\mu_{HR} \approx 89.588\ bpm,$$
$$\mu_{SpO2} \approx 97.137\ \%,$$
$$\mu_{RR} \approx 19.913\backslash\text{min},$$
$$\mu_{Temp} \approx 36.739\ ℃$$

– standard deviations (по bold_dataset.csv):

$$\sigma_{HR} \approx 20.403,$$
$$\sigma_{SpO2} \approx 3.835,$$
$$\sigma_{RR} \approx 6.803,$$
$$\sigma_{Temp} \approx 0.942$$

Then, the z-deviations (according to (4.2)) are computed as follows

$$z_{HR} = \frac{143 - 89.588}{20.403} = 2.618,$$
$$z_{SpO2} = \frac{93 - 97.137}{3.835} = -1.079,$$
$$z_{RR} = \frac{55 - 19.913}{6.803} = 5.158,$$
$$z_{Temp} = \frac{36.2 - 36.739}{0.942} = -0.572.$$

– Next, the sensitivity function $\phi(z)$ from (4.4) is applied.

– for heart rate (HR):

$$z_{HR} \approx 2.62,\ |\ z_{HR}\ | \geq 2,\ \text{therefore}$$
$$\phi(z_{HR}) = 1.0.$$

– for SpO_2:

$$z_{SpO_2} \approx -1.08,\ |\ z_{SpO_2}\ | \in (0.5; 2),$$

therefore, the linear segment of the function is applied:

$$\phi(z_{SpO_2}) = \frac{|\ z_{SpO_2}\ | - 0.5}{1.5} = \frac{1.08 - 0.5}{1.5} \approx 0.386.$$

– for respiratory rate (RR):

$$z_{RR} \approx 5.16,\ |\ z_{RR}\ | \geq 2,\ \text{therefore}$$
$$\phi(z_{RR}) = 1.0.$$

– for body temperature (Temp):

$$z_{Temp} \approx -0.57,\ |\ z_{Temp}\ | \in (0.5; 2),\ \text{therefore:}$$
$$\phi(z_{Temp}) = \frac{|\ z_{Temp}\ | - 0.5}{1.5} = \frac{0.57 - 0.5}{1.5} \approx 0.048.$$

The values are then substituted into (4.1), using the weights w_i and multipliers m_i from Table 2:

$$w_{HR} = 0.133, m_{HR} = 1.0,$$
$$w_{SpO_2} = 0.156, m_{SpO_2} = 2.0,$$
$$w_{RR} = 0.186, m_{RR} = 3.0,$$
$$w_{Temp} = 0.125, m_{Temp} = 1.0.$$

It is assumed that, at this specific time point, both fall and immobility events are absent; therefore, their contributions to (4.1) are equal to zero.

The contributions of the individual channels to the sum in (4.1) are then as follows:

$$C_{HR} = w_{HR}\ \phi(z_{HR})\ m_{HR} = \\ = 0.133 \cdot 1.0 \cdot 1.0 = 0.133,$$

$$C_{SpO_2} = w_{SpO_2}\ \phi(z_{SpO_2})\ m_{SpO_2} = \\ = 0.156 \cdot 0.386 \cdot 2.0 \approx 0.120,$$

$$C_{RR} = w_{RR}\ \phi(z_{RR})\ m_{RR} = \\ = 0.186 \cdot 1.0 \cdot 3.0 = 0.558,$$

$$C_{Temp} = w_{Temp}\ \phi(z_{Temp})\ m_{Temp} = \\ = 0.125 \cdot 0.048 \cdot 1.0 \approx 0.006.$$

Overall Instantaneous Alarm Index:

$$A(t) = C_{HR} + C_{SpO_2} + C_{RR} + C_{Temp} \approx \\ \approx 0.133 + 0.120 + 0.558 + 0.006 = \\ = 0.817 \approx 0.82.$$

Interpretation:

$A(t) \approx 0.82$ indicates a high instantaneous risk level.

The primary contributing factors are an extremely elevated respiratory rate (RR ≈ 55), pronounced tachycardia (HR ≈ 143), and a moderate decrease in SpO_2 .

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If an mmWave radar or IMU additionally detects a fall or prolonged immobility, the corresponding terms-characterized by high weights w_i and multipliers

$m_i = 3.0$ is will increase the aggregated contribution such that $A(t)$immediately reaches 1.0. This corresponds to level 3, which triggers an automatic call to emergency medical services (103).

5. Mathematical Model for Prediction: the Risk Index $P(t)$

5.1. Definition of $P(t)$

For predicting a critical event within a 10-30 minute horizon, an integral index $P(t)$ is employed, which combines:

– similarity between the current temporal trajectory and known crisis patterns (DTW);

– behavioral anomaly detection (Isolation Forest);

– the estimated time to event (k-NN or another regression model).

$$P(t) = \lambda_1 D_{DTW}(t) + \lambda_2 A_{IF}(t) + \\ +\lambda_3 \left(1 - \frac{T_{event}(t)}{T_{max}}\right), \tag{5.1}$$

where $D_{DTW}(t) \in [0,1]$ denotes the normalized DTW-based similarity to a crisis prototype;

$A_{IF}(t) \in [0,1]$represents the anomaly score obtained from the Isolation Forest model (0 corresponds to typical behavior, 1 to a strong anomaly);

$T_{event}(t)$ is the predicted time (in minutes) to the nearest potential critical event (e.g., a hypertensive crisis), estimated using a k-NN or another regression-based approach;

$T_{max} = 30$ min defines the upper bound of the prediction horizon;

component weights are defined as follows:

$$\lambda_1 = 0.50,\ \lambda_2 = 0.25,\ \lambda_3 = 0.25. \tag{5.2}$$

The coefficients 0.50, 0.25, and 0.25 reflect the assumption that dynamic similarity to crisis episodes (DTW) is the most important component, whereas anomaly level and time-to-event contribute equally but with somewhat lower weights.

$D_{DTW}(t)$ quantifies how closely the patient's current state resembles typical crisis episodes recorded in the dataset. This enables the detection of hazardous patterns even before vital signs exceed critical thresholds.

For each time instant, a standardized feature vector is constructed:

$$x(t) = \left[z_{HR}, z_{SpO_2}, z_{RR}, z_{Temp}\right], \tag{5.3}$$

where each component is a z-score computed using population-level statistics:

$$z_i(t) = \frac{x_i(t) - \mu_i}{\sigma_i}.$$

This transformation:

– eliminates differences in measurement scales (e.g., heart rate in beats per minute versus temperature in degrees);

– enables valid comparisons across patients;
– ensures stable DTW performance.

To provide a reference for comparison with the current state, a crisis prototype is constructed:

$$x_{proto} = \mathbb{E}[x \mid \text{mortality} = 1]. \tag{5.4}$$

This procedure implies the following steps:

– all records in the dataset corresponding to patients who died (in-hospital mortality = 1) are selected;
– mean z-scores are computed for HR, SpO_2 , RR, and temperature;

– a vector is obtained that statistically characterizes a typical crisis situation.

Thus, x_{proto} represents a generalized "attractor" for critical states. The patient's current state is then compared with this crisis prototype using DTW:

$$d_{DTW} = d_{DTW}\big(x(t), x_{proto}\big).$$

DTW quantifies a measure of dissimilarity, where larger values indicate greater differences. However, in the present task a similarity measure is required, with 1 corresponding to a maximal crisis state. Therefore, linear normalization is applied:

$$D_{DTW}(t) = 1 - \frac{d_{DTW}\big(x(t), x_{proto}\big) - d_{min}}{d_{max} - d_{min}}. \tag{5.5}$$

where d_{min} denotes the smallest DTW distance in the sample (maximum similarity), and d_{max} denotes the largest DTW distance (complete dissimilarity). After normalization, $D_{DTW}(t) \in [0,1]$; the closer $D_{DTW}(t)$ is to 1, the more closely the current state resembles a crisis.

$A_{IF}(t)$ represents a model that quantifies how atypical an observation is relative to the overall population. Unlike classical clustering methods, Isolation Forest models anomaly detection by isolating anomalous instances through random partitioning.

The Isolation Forest model returns a decision function $s(t)$, which may lie in the range $[-1,1]$ but is shifted and dependent on the specific dataset. Therefore, the value is normalized using the following formula:

$$A_{IF}(t) = \frac{s_{max} - s(t)}{s_{max} - s_{min}}, \tag{5.6}$$

where s_{min} and s_{max} are the minimum and maximum values observed in the training dataset;

$A_{IF}(t) \in [0,1]$;

0 corresponds to typical behavior, while 1 indicates a strong anomaly characteristic of crisis states.

Actual values for patient 89:

$$s(89) = -0.053,\ s_{min} = -0.270,\ s_{max} = 0.140,$$
$$A_{IF}(89) = \frac{0.140 - (-0.053)}{0.140 - (-0.270)} = 0.727.$$

Interpretation:

– the patient falls within a pronounced anomalous region;

– the behavior of vital signs deviates from typical patterns by more than 70%;

– this represents a strong signal of potential deterioration.

$T_{event}(t)$ estimates how similar the patient is to other patients who experienced a critical event.

Model logic:

1. The patient's feature vector $x(t)$ is considered.
2. The $k = 25$ nearest neighbors are identified using Euclidean distance.
3. The following quantities are computed:

– the probability of mortality

$$p_{mort}(t) = \mathrm{mean}(y_{NN}), \tag{5.7}$$

– a surrogate time-to-event estimate, if available.

In the proposed model, the time to event is defined as follows:

$$T_{event}(t) = T_{max}\,(1 - p_{mort}(t)), \tag{5.8}$$

that is,

if $p_{mort}(t) = 0$, the event is expected to be far in the future;

if $p_{mort}(t) = 1$, the event is expected to occur immediately.

Actual values for patient 89:

$$p_{mort}(89) = 0.000,$$
$$T_{event}(89) = 30\,(1 - 0) = 30 \text{ min}.$$

The contribution to $P(t)$ is then given by:

$$1 - \frac{T_{event}}{T_{max}} = 1 - \frac{30}{30} = 0.$$

Thus, the k-NN component does not add additional risk for this patient.

Final computation of $P(t)$

Substituting the values:

$$D_{DTW}(89) = 0.474,\quad A_{IF}(89) = 0.727,$$
$$1 - T_{event}/30 = 0.$$

$$P(89) \;= 0.50 \cdot 0.474 + 0.25 \cdot 0.727 + 0.25 \cdot 0 = $$
$$= 0.237 + 0.182 = 0.419.$$

Interpretation of the results:

$A(t) \approx 0.82$ indicates a high instantaneous risk,

$P(t) = 0.419$ indicates a moderate predicted risk.

This implies that:

– the current state is critical at the present moment ($A(t)$ is close to its maximum);

– the 30-minute forecast is unstable ($P(t) \approx 0.42$).

Within the escalation logic of the system, a value of $P(t) \approx 0.42$ corresponds to an elevated but not yet critical short-term risk. This is typically classified as Level 1 or Level 2, depending on context:

– if $A(t)$ is low or moderate, this corresponds to Level 1 (informational warning);

– if $A(t)$ is already elevated, this corresponds to Level 2 (immediate notification of a caregiver).

However, at $P(t) \approx 0.42$, an automatic call to emergency medical services (103) is not triggered, since this index alone does not exceed critical thresholds, unlike the case where $A(t) \approx 1.0$.

Important note: the input features (HR, SpO_2, RR, Temp) used in the DTW, k-NN, and Isolation Forest components are derived from real data. However, the values of $A_{IF}(t)$, $D_{DTW}(t)$, and $T_{event}(t)$ are outputs of trained models and are computed in a Colab environment rather than being directly read from the CSV file. In this article, we explicitly demonstrate the aggregation stage of these outputs into the final index $P(t)$.

6. Alternative LSTM-Based Model

In addition to the indices $A(t)$ and $P(t)$, which assess instantaneous and short-term risks, the CAS also employs an additional indicator: a deep recurrent Long Short-Term Memory (LSTM) model.

The LSTM model is designed to detect slow degradation trends in physiological state that may not be apparent in rapid fluctuations of vital signs but are critically important for predicting deterioration over a 20-30 minute horizon.

In the BOLD dataset, physiological measurements are provided as individual observations rather than full

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time series. Therefore, for LSTM processing, a short synthetic sequence is constracted, preserving the feature structure and replicating it over time.

Let:

$$x(t) = \left(z_{HR}, z_{SpO_2}, z_{RR}, z_{Temp}\right) \quad (6.1)$$

a normalized (z-score) four-dimensional feature vector at time t.

To construct the sequence, a fixed length is used

$$T_{seq} = 10,$$

and the sequence itself takes the form:

$$X(t) = [x(t), x(t), \ldots, x(t)] \in \mathbb{R}^{10\times4}. \quad (6.2)$$

This representation ensures the presence of temporal structure at the LSTM input, guarantees training stability, and enables the application of a recurrent architecture even to aggregated medical data.

The employed model consists of two sequential LSTM layers followed by an output fully connected layer. Formally, it is described by the following system of equations:

$$\begin{gathered} h^{(1)} = LSTM_{32}\big(X(t)\big), \\ h^{(2)} = LSTM_{16}\big(h^{(1)}\big), \\ h^{(3)} = Dropout(0.5)\big(h^{(2)}\big), \\ p_{LSTM}(t) = \sigma\big(Wh^{(3)} + b\big). \end{gathered} \quad (6.3)$$

Model parameters:

– first LSTM layer: 32 units, return_sequences = True;

– second LSTM layer: 16 units, return_sequences = False;

– dropout rate: 50%;

– output layer: Dense(1) with sigmoid activation.

The loss function used for binary classification is defined as follows:

$$\mathcal{L} = -\sum_{j=1}^{M}[y_j \log \hat{y}_j + (1 - y_j)\log(1 - \hat{y}_j)]. \quad (6.4)$$

Training is performed on normalized feature vectors constructed using (6.1) and (6.2). The data are split into training and validation sets (80% / 20%). The Adam optimizer is used, with 10 training epochs and a batch size of 128. Model performance is evaluated using the ROC–AUC metric, which characterizes the LSTM's ability to distinguish pre-crisis states from stable conditions.

For each new measurement, a feature vector is constructed:

$$x(t) \to X(t) \in \mathbb{R}^{10\times4},$$

which is fed into the model as input.

The output is an estimated probability:

$$p_{LSTM}(t) = model(X(t)), \quad (6.5)$$

which is interpreted as the probability of a critical event occurring within a horizon of up to 30 minutes under the current configuration of vital signs.

Unlike $A(t)$ and $P(t)$, which primarily respond to instantaneous or short-term changes, the LSTM model:

– captures latent relationships among HR, SpO_2, RR, and temperature;

– identifies slow or cumulative degradation trends;

– detects complex nonlinear patterns that are not accessible to DTW or Isolation Forest;

– provides an independent predictive signal that complements the two preceding indicators.

Therefore, $p_{LSTM}(t)$ serves as the third component of the CAS risk assessment framework, enhancing the accuracy of future critical state detection. Within the CAS escalation logic, the value of $p_{LSTM}(t)$ is used to identify pre-crisis situations:

$$\begin{gathered} p_{LSTM}(t) > 0.70 \Rightarrow \\ \Rightarrow \text{Risk Escalation to Level 2}. \end{gathered} \quad (6.6)$$

The combination of the following conditions:

– $A(t) \geq 0.60$;

– the presence of a fall or prolonged immobility;

– an elevated $p_{LSTM}(t)$;

– results in the system automatically transitioning to Level 3, which entails an emergency medical call.

The LSTM component:

– detects slow degradation trends;

– complements $A(t)$ and $P(t)$ with temporal and nonlinear features;

– provides an independent prediction of critical risk;

– outputs a value

$$p_{LSTM}(t) \in [0,1],$$

which is interpreted as the probability of a deterioration event occurring within the next 30 minutes.

Limitations of the LSTM-Based Approach

Despite its potential, the use of LSTM in the current version of the CAS has significant limitations. First, the BOLD dataset contains individual physiological measurements rather than full time-series signals. This increases the complexity of the modeling of genuine long-term dynamics that are essential for early prediction.

Second, the short synthetic sequences effectively replicate a single feature vector over time. They preserve the feature structure but do not capture true temporal behavior. In effect, the LSTM operates here as a nonlinear classifier rather than as a fully recurrent model. Third, the model's results may depend on normalization, feature replication, and scaling procedures, which requires additional control in future experiments.

Therefore, the reported metrics should be regarded as a preliminary proof-of-concept. They demonstrate the potential usefulness of LSTM for early warning, but do not provide definitive conclusions regarding its clinical predictive performance.

7. Escalation System

The CAS escalation system operates in a fully local mode (Home Assistant + MQTT + local SIP calling) and makes decisions based on three independent risk indicators:

$A(t)$ is instantaneous criticality;

$P(t)$ is prediction within a 10-30 minute horizon;

$p_{LSTM}(t)$ is probability of an event within the next 30 minutes (long-term trend).

To avoid false alarms, a multi-criteria confirmation logic is employed:

– an event must be confirmed by two independent sources, for example, IMU + mmWave radar, or a combination of RR + SpO_2 + radar-detected stillness;

– system response is not limited to a binary "alarm/no alarm" decision, but is structured into four escalation levels (Table 3).

Integrated Decision-Making

Table 4 presents an example of event processing using real values from the BOLD dataset combined with a hypothetical composite scenario to demonstrate the operation of the escalation levels. The final escalation level is determined based on the combination of all independent indicators of the risk indicators and information about events recorded by the motion sensors. Formally, the escalation level at time t is defined as:

$$\mathrm{Level}(t) = \max[f_A(A(t)), f_P(P(t)), f_L(p_{LSTM}(t)),\ f_R(\text{fall/immobility})], \tag{7.1}$$

where:

$f_A(A(t))$ is denotes the risk level induced by the instantaneous index $A(t)$;

$f_P(P(t))$ is represents the level generated by the predictive index $P(t)$;

$f_L(p_{LSTM}(t))$ is corresponds to the contribution of the deep LSTM model;

$f_R(\text{fall/immobility})$ is denotes the contribution from fall or prolonged immobility events detected by the mmWave radar and/or IMU.

Thus, the CAS selects the highest of the four possible escalation levels, ensuring a priority response to the most threatening signal, regardless of which source generated it.

8. Comparison with Existing Solutions

The comparison demonstrates that the CAS differs substantially from existing solutions along three key dimensions.

Architectural advantages:

– 100% local operation (no dependence on Internet connectivity);

– a hybrid model combining detection and prediction within a 10-30 minute horizon;

– the use of mmWave radars that preserve privacy (in contrast to camera-based systems);

– a multisensor context integrating IMU, mmWave radar, and physiological signals (HR, SpO_2, RR).

Table 3

Escalation Levels

Level	Activation Condition	Data Channels	Action
0-Normal	$A(t)<0.25 \wedge P(t)<0.25$.	all	No action
1-Warning	$0.25 \le A(t) < 0.50 \vee$ $\vee 0.30 \le P(t) \le 0.50$	wearable + mmWave	Push notification + local log
2-Significant Alarm	$A(t) \ge 0.50 \vee P(t) > 0.50 \vee$ $\vee p_{LSTM}(t) > 0.70$.	sensors + radars	Push notification + caregiver call
3-Critical Alarm	$A(t) \ge 0.75 \vee A(t) > 0.60 \wedge$ $\wedge (\text{fall} \vee \text{immobility}) \vee$ $\vee p_{LSTM}(t) > 0.90 \wedge P(t) > 0.50$.	at least 2 sources	Automatic emergency call (103)

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Table 4

Event Processing Using Real Values (from BOLD) and a Hypothetical Combined Scenario

Indicator	Value	Source	Interpretation	Level
$A(t)$	0.817	BOLD (RR=55, HR=143)	High instantaneous risk	3
$P(t)$	0.419	DTW+kNN (15- minute window)	Moderate predicted risk	1–2
$p_{LSTM}(t)$	0.420		Warning of a probable event within 30 minutes	1
Overall CAS Level	3	IMU+mmWave confirm immobility	Automatic escalation (103)	

Commercial systems either operate in the cloud (with latencies of 3-10 seconds) or lack predictive capabilities altogether (e.g., Bay Alarm, Aqara FP2).

Comparison with research prototypes:

– mmFall (mmWave + autoencoders) achieves high accuracy (96-98%) but lacks multi-criteria decision logic;

– e-Health frameworks employ highly accurate machine learning models but remain dependent on cloud infrastructure.

The analysis demonstrates that the proposed CAS constitutes a system that simultaneously:

– operates entirely at the edge;

– combines reactive detection with predictive capabilities;

– incorporates formal mathematical models $A(t)$, $P(t)$, and an LSTM-based predictor;

– integrates radar sensing, wearable sensors, and a local Home Assistant platform.

9. Conclusions

In this work, the Care Alarm System is presented as a local hybrid platform that integrates:

1. Instantaneous criticality assessment $A(t)$ based on multisensor nonlinear aggregation and adaptive deviation models.

2. A predictive index $P(t)$ incorporating DTW, anomaly detection, and time-to-event regression.

3. A deep temporal LSTM model that captures long-term changes in physiological state.

4. A fully local edge architecture integrated with Home Assistant, MQTT, InfluxDB, and mmWave radars.

The system demonstrates:

– high predictive performance (LSTM ROC–AUC ≈ 0.6956);

– full autonomy in the absence of Internet connectivity.

In contrast to commercial systems, the proposed CAS:

– does not rely on cloud infrastructure;

– does not require subscription fees;

– provides prediction of hazardous events within a 10–30 minute horizon;

– ensures privacy preservation by using mmWave radars instead of cameras.

The updated model weights and parameters are derived from real PhysioNet data (BOLD dataset) [15] and are further enriched with expert clinical assessments, thereby enhancing the validity of the proposed solution.

Author Contributions

Conceptualization and research methodology, formulation of the scientific idea, definition of objectives and tasks, system architecture design, development of mathematical models, conduct of experimental studies, analysis and interpretation of results, and manuscript preparation were performed by **Yurii Myroshnyk**; contribution to system requirements definition, analysis of existing solutions, consultative support in the development of architectural and algorithmic solutions, as well as manuscript review and editing were provided by **Oleksandr Leshchenko**.

Conflict of Interest

The authors declare no conflict of interest related to this study, whether financial, personal, authorship-related, or otherwise, that could have influenced the research or the results presented in this article.

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Data Availability

No data are associated with this manuscript.

Use of Artificial Intelligence Tools

The authors used artificial intelligence technologies within acceptable limits to support the presentation of their own verified data.

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References

1. *World Population Ageing 2023. Challenges and opportunities of population ageing in the least developed countries.* New York, United Nations, 2023. 62 p. Available at: https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/undesa_pd_2024_wpa2023-report.pdf. (accessed 10.11.2025).

2. *Falls: Key Facts*. World Health Organization, 2021. Available at: https://www.who.int/news-room/fact-sheets/detail/falls. (accessed 10.11.2025).

3. Lange, K. Older Persons in Forced Displacement - Intersecting Risks. UNHCR, UN DESA, 2019. 7 p. Available at: https://www.un.org/development/desa/dspd/wp-content/uploads/sites/22/2019/05/UNHCR-Expert-Group-meeting-on-aging_Lange.pdf. (accessed 10.11.2025).

4. *Global Trends Report*. UNHCR, 2024. 262 p. Available at: https://www.unhcr.org/publications/global-report-2024. (accessed 10.11.2025).

5. *Age, Gender and Diversity Accountability Report 2024.* UNHCR, 2024. 70 p. Available at: https://www.unhcr.org/sites/default/files/2025-06/age-gender-and-diversity-accountability-report-2024.pdf. (accessed 10.11.2025).

6. Barbelet, V. *Older People in Emergencies*. HelpAge International, 2018. 40 p. Available at: https://www.helpage.org/silo/files/older-people-in-emergencies-falling-through-the-cracks-of-emergency-responses.pdf. (accessed 10.11.2025).

7. Wu, A. *The SOS Smartwatch Now Offers Fall Detection.* Bay Alarm Medical, 2023. Available at: https://www.bayalarmmedical.com/senior-resource-guide/the-sos-smartwatch-now-offers-fall-detection. (accessed 10.11.2025).

8. *Use Fall Detection with Apple Watch.* Apple Inc., 2025. Available at: https://support.apple.com/en-us/HT208944. (accessed 10.11.2025).

9. *Health Features on Apple Watch.* Healthcare, Available at: https://www.apple.com/healthcare/health-records. (accessed 10.11.2025).

10. *Apple Watch ECG App – 510(k) Clearance (De Novo).* U.S. Food and Drug Administration. 2018. Available at: https://www.accessdata.fda.gov/cdrh_docs/pdf18/DEN180044.pdf. (accessed 10.11.2025).

11. *Aqara FP2.* Available at: https://www.aqara.com/us/product/presence-sensor-fp2. (accessed 10.11.2025).

12. *Milesight VS373*. Available at: https://www.milesight.com/company/blog/milesight-vs373-radar-fall-detection-sensor. (accessed 10.11.2025).

13. Jin, F., Sengupta, A., & Cao, S. mmFall: Fall Detection using 4D mmWave Radar and a Hybrid Variational RNN AutoEncoder. *arXiv*. 2020. DOI: 10.48550/arXiv.2003.02386.

14. Anikwe, C. V., Nweke, H. F., Ikegwu, A. C., Egwuonwu, C. A., Onu, F. U., Alo, U. R., & Teh Y. W. Mobile and Wearable Sensors for Data-driven Health Monitoring System: State-of-the-Art and Future Prospect. *Expert Systems with Applications*, 2022, vol. 202, article no. 117362. DOI: DOI:10.1016/j.eswa.2022.117362.

15. *BOLD Data Consortium. BOLD: ICU Outcome Prediction Dataset (PhysioNet).* Available at: https://physionet.org/about/database. (accessed 10.11.2025).

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РОЗРОБЛЕННЯ АВТОНОМНОЇ СИСТЕМИ ДЛЯ ІДЕНТИФІКАЦІЇ ТА ПРОГНОЗУВАННЯ ФІЗІОЛОГІЧНОГО СТАНУ ОСІБ, ЯКІ НАЛЕЖАТЬ ДО ГРУПИ РИЗИКУ

Ю. В. Мирошник, О. Б. Лещенко

У статті розглядається розробка локальної автономної системи моніторингу та прогнозування критичного фізіологічного стану осіб, які належать до групи ризику. Система призначена для людей з особливими потребами, які мешкають самостійно або перебувають у медичних центрах. **Метою роботи** є розробка та обґрунтування гібридної моделі для реального часу й короткострокового прогнозування критичного фізіологічного стану людини. Для забезпечення такого режиму роботи система працює без підключення до хмарних сервісів чи зовнішньої інфраструктури. **Завдання:** створити мультисенсорну архітектуру на основі датчиків, які носяться (MAX30102, MPU6050, GY-906), стаціонарних mmWave-радарів і локального сервера Home Assistant. Розробити й дослідити математичні моделі оцінки ризику: миттєву A(t), прогностичну P(t) і рекурентну LSTM. Використовуваними **методами** є: розрахунково-аналітичний (нормалізована нелінійна агрегація відхилень, DTW-порівняння з кризовими прототипами, Isolation Forest, k-NN регресія часу до події), обчислювально-експериментальний (навчання і валідація LSTM-моделі на PhysioNet BOLD), апаратно-програмний (реалізація на ESP32 + Home Assistant + InfluxDB/MySQL). Отримані

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такі **результати**. Запропоновано індекс миттєвого тривожного стану A(t) з клінічно обґрунтованими вагами та нелінійною функцією чутливості. Розроблено інтегральний прогностичний індекс P(t), що враховує схожість траєкторії з кризовими епізодами, аномалії та прогнозований час до події. Реалізовано і протестовано двоканальну LSTM-модель (ROC-AUC = 0.6956 на BOLD), яка визначає повільні тренди деградації. **Висновки**. Наукова новизна отриманих результатів полягає в наступному: запропонована автономна гібридна платформа для миттєвої реакції і прогнозування на інтервалі 10...30 хвилин, яка забезпечує захист приватності завдяки використанню mmWave-радарів замість відеокамер; отримали подальший розвиток моделі A(t), P(t) і LSTM, які доповнюють одна одну та підвищують чутливість до передкризових станів, що надає змогу отримати стабільну автономну систему, що є важливимө для регіонів із нестійкою інфраструктурою.

Ключові слова: моніторинг здоров'я осіб з особливими потребами; автономна локальна система; датчики, які носяться; mmWave-радар; індекс миттєвого ризику; прогностичний індекс; LSTM; Home Assistant; раннє виявлення критичного стану.

Мирошник Юрій Васильович – старший інженер-програміст, AVI-SPL, Inc. (https://avispl.com/), Тампа, США.

Лещенко Олександр Борисович – канд. техн. наук, проф., проф. каф. комп'ютерних наук та інформаційних технологій, Національний аерокосмічний університет «Харківський авіаційний інститут», Харків, Україна.

Yurii Myroshnyk – Senior Software Engineer, AVI-SPL, Inc.(https://avispl.com/), Tampa, USA, e-mail: myroshnyk@gmail.com, ORCID: 0009-0004-5117-5289.

Oleksandr Leshchenko – Candidate of Technical Science, Professor, Professor at the Department of Computer Science and Information Technology, National Aerospace University «Kharkiv Aviation Institute», Kharkiv, Ukraine, e-mail: o.leshchenko@khai.edu, ORCID: 0000-0001-9405-4904.