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Non-Intrusive Sensor-Based Sleep Monitoring and Machine Learning Classification for Individuals with Disabilities in Residential Facilities: A Case Study from the MetaSalute Project

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***Abstract*—The growing ageing population calls for non-intrusive monitoring frameworks capable of supporting the continuous assessment of frail individuals in real-world care settings. This paper presents a machine-learning-based approach for classifying nocturnal health conditions using physiological measurements acquired through bed-based sensors in long-term care facilities. Developed within the MetaSalute project, the study considers data collected from November 2025 to March 2026 through bed-bands installed in three residential care facilities, allowing the monitoring of 27 subjects. Caregiver-reported questionnaires were used to derive binary labels by assigning a class to each answer. Heart rate and respiratory rate signals were aggregated into one-hour windows, transformed into statistical descriptors, and normalized on a subject-specific basis. A Balanced Random Forest classifier was then trained to address the class imbalance typical of real-world clinical monitoring data. The model achieved a balanced accuracy of 79.7% and a ROC AUC of 0.84, showing good capability in detecting critical nocturnal events.**

***Index Terms*—Internet of Things, Ambient Assisted Living, Machine Learning, Night-time Monitoring, Elderly Care**

I. Introduction

The increase in life expectancy represents one of the most significant achievements of scientific, technological, and medical progress over the last century. According to recent global demographic projections, the number of people aged over 60 is expected to double by 2050, exceeding 2 billion worldwide [1]. To address these demands, healthcare systems are increasingly embracing the Industry 5.0 paradigm. This transition shifts the focus from pure digitalization to human-centric ecosystems [2]. In this context, the paradigm of Ambient Assisted Living (AAL) has emerged as a promising approach to support active and healthy ageing. AAL refers to a set of technology-driven solutions aimed at enhancing the quality of life of older adults and people with disabilities through intelligent and non-invasive systems. Technologies enabling AAL systems can be broadly classified into three main categories: wearable sensors, environmental sensors, and activity monitoring systems [3]. Wearable devices represent one of the most widely adopted solutions for monitoring physiological parameters [4]. Environmental sensors, on the other hand, provide contextual information related to indoor conditions [5]. Finally, activity monitoring systems enable the detection and analysis of user behavior [6]. Artificial intelligence plays a central role in AAL systems. Recent studies have demonstrated the potential of AI-based approaches, such

as artificial neural networks, to monitor elderly individuals' activities and provide adaptive, automated assistance [7]. AAL ecosystems involve multiple stakeholders, including not only patients but also caregivers, healthcare professionals, social services, and care organizations [8]. These systems typically address a wide range of functionalities. It is essential to distinguish between different living environments, such as private homes and residential care facilities, as well as between individuals living alone or with caregivers or family members [9]. Despite the growing body of research on AAL systems combined with AI models, a relevant gap remains in the literature: the lack of studies focusing on nocturnal monitoring through non-intrusive sensors in residential care settings, combined with clinically meaningful labels derived from caregiver observations. Existing works often rely on controlled environments, synthetic labels, or wearable-based monitoring, which may limit scalability, patient compliance, and real-world applicability. This work addresses this gap by investigating whether bed-based nocturnal physiological signals, collected in three different real-world residential care facilities, can be used to reliably classify nocturnal conditions through a machine learning pipeline. This study was carried out within the MetaSalute project which delivered an integrated monitoring system for frail individuals, The project was conceived to support the continuous collection and management of physiological, behavioral, and environmental information in real socio-healthcare settings, thus providing the technological basis for the development of focused monitoring pipelines tailored to specific clinical or assistive scenarios. Nocturnal alterations, in frail older adults, may reflect or anticipate changes in clinical status, behavioral instability, sleep disturbances, or worsening physiological conditions [10]. This paper presents a case study on night-time monitoring in residential care based on physiological measurements acquired through non-intrusive bed-based sensors and on caregiver-informed labels. The study involves residents hosted in three residential care facilities within the MetaSalute project and focuses on the classification of nocturnal conditions through a Machine Learning (ML) model trained on sensor-derived statistical descriptors. The proposed approach aims to identify critical nocturnal conditions from continuous physiological measurements acquired in real-world long-term care settings. The remainder of this paper is organized as follows. Section II provides an overview of the related work. Section III details the adopted methodology, and the machine learning classification pipeline. Section IV presents and discusses the experimental results and finally Section V concludes the work and outlines future research directions.

II. Related work

In this section, we provide a brief overview of the current state of the art in night-time monitoring of geriatric patients.

A. Night-Time Monitoring in Elderly Care

Night-time monitoring represents a critical aspect of elderly care, as patients are particularly vulnerable to adverse events such as falls, wandering, and undetected clinical deterioration during sleep hours. A recent scoping review by Hotta et al. [11] categorized night-time monitoring and intervention strategies into five main areas: (i) night-time medical emergency team or rapid response team (MET/RRT) interventions, (ii) night-time observation based on Early Warning Scores (EWS), (iii) availability of clinical resources for physicians, (iv) continuous monitoring of specific physiological parameters, and (v) screening for night-time clinical deterioration. Their findings highlight both the complexity of night-time care and the limitations of current practices, particularly in terms of timely detection and intervention. For instance, Cheung et al. proposed the eNightLog system, a non-contact sensing platform based on time-of-flight and ultra-wideband sensors, capable of detecting bed-exiting events and abnormal nocturnal behaviors with high accuracy [12]. Beyond event detection systems, research has also focused on understanding nocturnal motor and behavioral alterations in clinical populations. A recent systematic review by Li et al. [13] highlighted its strong correlation with disease severity, sleep disturbances, and reduced quality of life, emphasizing the importance of continuous night-time monitoring. Several studies have investigated different sensing approaches for night-time monitoring, ranging from polysomnography, considered the gold standard for sleep analysis, to wearable and ambient sensors [14]. To further advance unobtrusive nocturnal monitoring, previous research ([15]), has successfully demonstrated the feasibility of extracting sleep-related parameters, and validated the metrological reliability of low-cost, contact-less setups for continuous sleep quality assessment in real-world scenarios.

B. Sensor-Derived Classification and Synthetic Indicators in Elderly Monitoring

The use of synthetic indices to summarize complex health conditions is well established in geriatric and clinical research. Among the most widely adopted approaches, frailty indices have played a central role in quantifying vulnerability in older adults [16]. In particular, the deficit accumulation model proposed by Rockwood conceptualizes frailty as the proportion of accumulated health deficits, providing a composite measure associated with adverse outcomes such as disability, hospitalization, and mortality [17]. More recently, electronic and hospital-based frailty scores have extended this concept in fact, the Hospital Frailty Risk Score was developed to identify older patients offering a systematic and low-cost screening tool [18]. Casaccia et al. proposed a framework for measuring users' well-being through domotic sensors and ML algorithms, showing that environmental and behavioral data can be translated into an interpretable well-being assessment [19]. Similarly, broader smart aging research has investigated the use of multimodal monitoring systems to infer hidden wellness patterns from physiological, behavioral, and environmental signals, further supporting the relevance of composite health indicators in elderly care [20]. Reviews on unobtrusive sensor-based frailty assessment have also highlighted the growing interest in moving from static clinical scales toward continuous

monitoring approaches based on wearable and ambient sensing technologies [21]. Taken together, these studies support the relevance of combining non-invasive sensing and data-driven analysis in elderly care. However, limited attention has been paid to frameworks specifically devoted to unobtrusive bed-based night-time monitoring in residential care environments.

III. Materials and Methods

An IoT-based ecosystem was deployed across five socio-healthcare facilities hosting frail individuals. As illustrated in the methodological pipeline (Fig.1), the data analysis workflow is structured into sequential and interconnected stages.

A. Overall project architecture

The overall architecture was conceived to support passive and continuous observation of users' physiological and behavioral conditions in everyday care settings, through an integrated IoT framework connecting sensing devices, data acquisition services, storage components, and operator-facing applications. At the architectural level, as shown in Fig. 2, the platform is centered on a centralized application responsible for collecting, integrating, and managing data from multiple heterogeneous sources. The architecture includes a central database, a data acquisition layer for sensor collection and preprocessing, the MetaSalute platform for data integration and service orchestration, a monitoring dashboard for healthcare operators, and a telemedicine workstation for remote clinical assessment. The operational status of the sensing devices is also monitored through dedicated endpoints in order to ensure system reliability and data quality. A comprehensive technical description of the proposed architecture and its underlying components is detailed in [22].

B. Case study: night-time bed-band monitoring

Although the MetaSalute ecosystem was designed as a broader multimodal platform, the specific scope of this study focuses on classifying the health status of frail patients during the night. This choice reflects the clinical relevance of unobtrusive nocturnal monitoring in vulnerable populations and the need to minimize user burden in long-term care environments. To achieve this objective, the methodological pipeline relies exclusively on continuous measurements acquired from sleep monitoring bed-bands installed in a subset of three residential facilities: Casa Giona, Dopo di Noi apartments, and Santa Colomba. Specifically, the analyzed dataset comprises recordings collected from 27 individuals over a monitoring period spanning from November 10, 2025, to March 5, 2026. Overall, the resulting dataset comprises 10832 hourly windows, corresponding to a total of 930 valid patient-nights. In terms of class distribution for the classification task, the dataset is highly imbalanced, reflecting real-world clinical conditions, with 10405 samples associated with normal nocturnal patterns and 427 samples representing critical events. Regarding the demographic characteristics of the 27 monitored subjects, the cohort spans a broad age range reflecting the specific care targets of the three facilities. Specifically, the analyzed sample includes 4 individuals from the Dopo di Noi apartments (aged 18 and older), 10 residents from Casa Giona (aged 25 and older), and 13 older adults from the Santa Colomba facility (aged over 65). The bed band adopted in the project is the Domethics Sleep Monitor Belt, a device positioned under the sheet and designed for passive overnight monitoring. The sensor supports the monitoring of heart-related and respiratory signals, nocturnal movements, and sleep-related information without requiring direct interaction from the user.

C. Ground-truth construction from caregiver questionnaires

To establish a reliable ground truth for supervised ML, the qualitative assessments provided by the caregivers through questionnaires were first translated into a quantifiable score and then binarized into the labels used for model training. Specifically, healthcare staff evaluated the psychophysical and behavioral status of the patients by completing one single questionnaire per day for each subject, from which two distinct evaluation indices, a daytime score and a nighttime score, were extracted. Each questionnaire consisted of four multiple-choice questions:

1) Were there behavioral changes during the day?

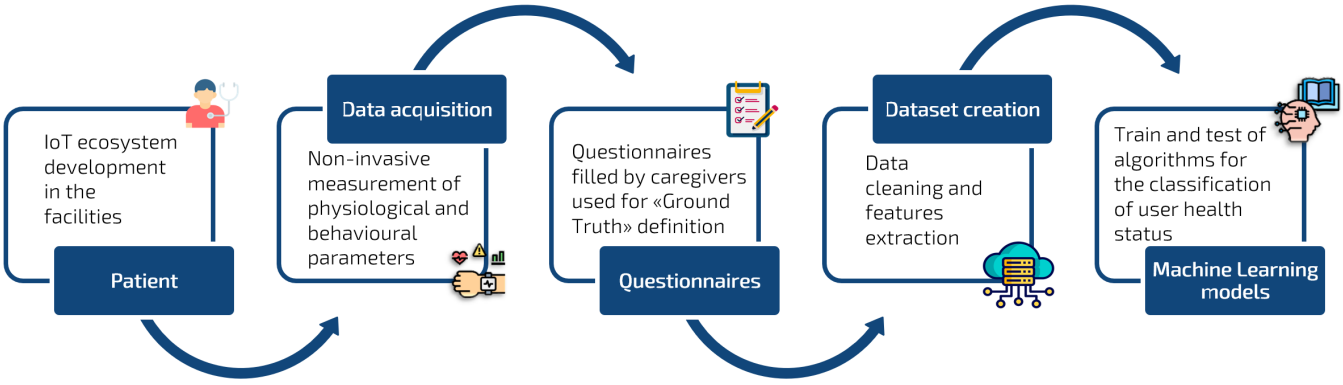


Fig. 1. Workflow of the adopted methodology.

2) Were there unusual behaviors during the night?
3) Were there observable improvements in the condition of the patient?
4) Were there variations in physiological parameters?

To compute the final labels, each specific multiple-choice answer was directly mapped a priori to either a normal or critical status based on clinical severity. The daytime label was derived by cross-referencing Question 1, 3, and 4, while the nighttime label was computed using Question 2, 3, and 4. A boolean logic approach was then applied: if the relevant subset of questions for a specific period contained at least one critical response (e.g., falls, psychomotor agitation, or altered vital signs), the corresponding label (daytime or nighttime) was assigned a Critical status. Conversely, if all answers in the subset indicated stable or improving conditions, a Normal label was assigned. Regarding temporal alignment, the binary label extracted for the day or the night was then uniformly applied to all the one-hour sensor windows belonging to that respective time window for that patient. This binary categorization provided the labeled dataset required to train the classification models to distinguish sensory patterns associated with stable health from those indicating potential risk.

D. Dataset creation

The sleep bed-band, equipped with internal pre-processing, delivers clean, pre-filtered streams sampled at 0.02 Hz (1 sample per minute) of two primary physiological parameters: Heart Rate (HR), Respiratory Rate (RR). To translate continuous physiological signals into informative features for the ML pipeline, a one-hour time window was utilized. An hourly window was considered valid and retained in the dataset only if it contained at least two samples. For each hourly segment, a set of statistical features was computed to summarize the distributions of cardiac and respiratory signals. The extracted features include:

- Heart Rate Features: Mean, Maximum, Minimum, Standard Deviation, Range and Coefficient of Variation
- Respiratory Rate Features: Mean, Standard Deviation, Range and Coefficient of Variation

Subsequently, a data normalization step was necessary to mitigate the impact of inter-subject variability, which could otherwise bias the classification model due to individual baseline physiological differences. To achieve this, Z-score standardization was applied to the extracted features on a per-subject basis. This process scales the feature distributions so that they represent relative physiological deviations rather than absolute values:

$$z = \frac{(x - \mu)}{\sigma} \tag{1}$$

where x represents the original hourly feature value, μ is the subject-specific mean computed over a two-month reference period classified as normal, and σ is the corresponding standard deviation obtained from that same baseline period. Specifically, this personalized baseline consists of the patient's first two months of recorded nights exclusively labeled as Normal. To ensure the statistical reliability of this reference period, a strict inclusion criterion was enforced: any subject who did not accumulate a minimum of two months of normal nights over the entire monitoring period was excluded from the final dataset.

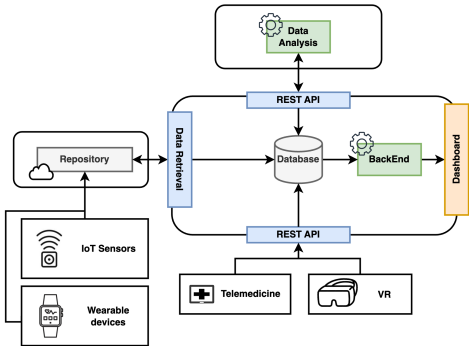


Fig. 2. Iot Ecosystem of MetaSalute project.

E. Machine Learning model description

To automatically classify the nocturnal health status of the monitored subjects, a supervised ML approach was implemented. The target variable was constructed by binarizing the previously computed score: an optimal score (indicating a normal and quiet situation) was encoded as the negative class (class 0), whereas any lower score (indicating a critical or anomalous situation) was encoded as the positive class (class 1). To rigorously evaluate the generalization capability of the algorithm, the dataset was partitioned into a training set (80%) and a testing set (20%). A stratified splitting technique was employed during this phase to preserve the original proportion of the classes within both subsets, preventing biased training distributions. Given the intrinsic nature of clinical monitoring datasets, where critical events are typically less frequent than normal physiological states, a Balanced Random Forest (BRF) classifier was selected. This ensemble learning method is specifically designed to handle imbalanced datasets by modifying the standard Random Forest algorithm. Furthermore, the sampling strategy was configured to balance all classes using bootstrap sampling with replacement, ensuring that each tree in the forest is trained on a perfectly balanced data sample. The predictive performance of the classifier on the test set was evaluated using a comprehensive suite of metrics, specifically: precision, recall, and the F1-score. Given the inherent class imbalance typical of clinical monitoring data, the Balanced Accuracy score was utilized as a primary evaluation criterion. This metric is defined as the arithmetic mean of sensitivity (True Positive Rate) and specificity (True Negative Rate), providing a highly reliable assessment of classification performance across both the majority and minority classes without being biased by the most frequent class:

$$BalancedAccuracy = \frac{Sensitivity + Specificity}{2} \tag{2}$$

The confusion matrix of the model was also reported. Furthermore, to evaluate the discriminatory capability of the

classifier across various decision thresholds, the Area Under the Receiver Operating Characteristic Curve (ROC AUC) score was computed. This quantitative metric was additionally complemented by plotting the corresponding ROC curve. Finally, to provide clinical interpretability, feature importance was estimated using the Mean Decrease in Impurity (Gini importance) criterion.

IV. Results and Discussion

The predictive performance of the Balanced Random Forest classifier was evaluated to assess its capability in distinguishing between normal sleep patterns and critical nocturnal events. Given the imbalanced nature of the dataset, the primary metric utilized to evaluate the overall performance was the Balanced Accuracy, which reached a value of 79.7%. This result indicates a robust capability of the model to correctly classify both the majority class (Normal) and the minority class (Critical) without being biased towards the most frequent instances. Detailed classification metrics, including Precision, Recall, and F1-score for both classes, are summarized in Table I. The analysis of these metrics reveals a distinct performance profile depending on the target class, highlighting the typical trade-offs encountered in highly imbalanced clinical datasets. For the Normal class, the classifier demonstrates excellent performance, characterized by a Precision of 0.99 and a solid Recall of 0.84. This yields a high F1-score of 0.91, indicating that predictions of normal nocturnal patterns are highly reliable and that the majority of actual normal nights are correctly identified. Conversely, the minority Critical class exhibits a high Recall of 0.75 alongside a low Precision of 0.16. The strong Recall value demonstrates that the system successfully detects 75% of actual nocturnal anomalies, effectively keeping the number of False Negatives very low. This minimizes the risk of the system missing a potentially dangerous health event. On the other hand, the low Precision is driven by a high number of False Positives, meaning the system frequently flags situations as critical even when they resolve safely. In the context of continuous healthcare monitoring, prioritizing sensitivity over precision is a standard safety protocol: triggering a preventive check by the healthcare staff (a false alarm) is inherently preferable to failing to detect a severe deterioration. The confusion matrix in Fig. 3 visually confirms this clinical trade-off while emphasizing the severe class imbalance characterizing the test set. Despite the overwhelming disproportion of actual Normal instances compared to Critical ones (2081 vs. 86), the model maintains a highly conservative behavior, missing only 21 anomalies (False Negatives) while accepting a larger volume of False

TABLE I
Balanced Random Forest classification metrics: precision, recall and f1-score

	Precision	Recall	F1-score
Normal	0.99	0.84	0.91
Critical	0.16	0.75	0.27

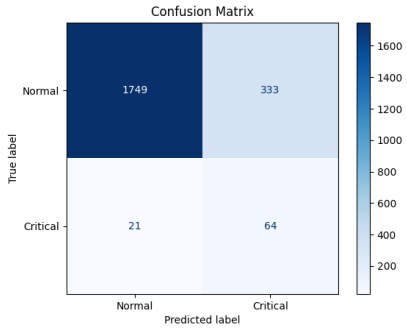


Fig. 3. Confusion Matrix.

Positives (325). To provide a more comprehensive evaluation of the performance of the classifier across different decision thresholds, a Receiver Operating Characteristic (ROC) analysis was conducted (Fig. 4) . The resulting curve, computed with respect to the Critical class, yields an Area Under the Curve (AUC) of 0.84, indicating a good overall discriminative ability. The ROC profile, characterized by a steep initial increase, is consistent with the Recall of 0.75 observed for critical events, confirming the ability of the model to identify the majority of true positive cases. However, this performance is achieved at the expense of a high false positive rate, as reflected by the low value of the Precision, highlighting a clear trade-off toward sensitivity. Furthermore, the feature importance analysis revealed that the mean respiratory rate is the most discriminative predictor of nocturnal anomalies (relative importance: 19.5 %), closely followed by the mean (11.6 %) and maximum (11.3 %) heart rates.

V. Conclusions and Limitations

The present work describes a ML approach to classify the health status of frail individuals during the night, utilizing data acquired from a non-intrusive monitoring system deployed in real-world long-term care facilities. a robust ground truth was formulated by translating qualitative caregiver assessments into a binary classification of the nocturnal status of the

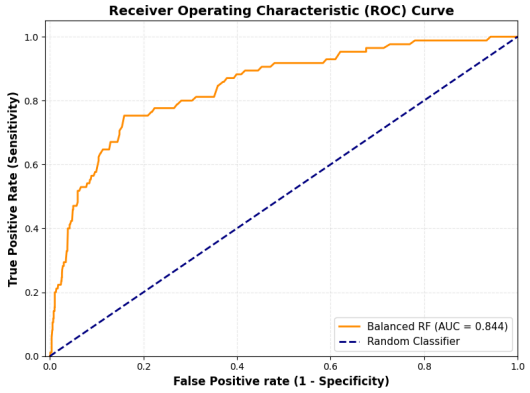


Fig. 4. Receiver Operating Characteristic (ROC) curve for the critical class.

patient. The results suggest that the proposed approach can assist in classifying the nocturnal health status of frail patients. While the model produces a notable number of false positives, its sensitivity toward critical events is a relevant outcome. By prioritizing the identification of nocturnal anomalies, the system aims to reduce the occurrence of missed health deteriorations. this technology can serve as a supplementary support tool for caregivers, providing additional nocturnal surveillance. Furthermore, these classification outputs can be leveraged to develop specific well-being indexes to provide meaningful and simple summary measures of the patient status. Despite these findings, the study presents some limitations. First, the dataset is constrained by a limited number of subjects and, most notably, a short monitoring period of only a few months. Second, the data is highly imbalanced, These factors may affect the statistical robustness of the reported performance, as the limited sample size and observation window can introduce variability in the estimation of the ROC AUC (0.84) and reduce the generalizability of the results. Therefore, the reported performance should be interpreted as indicative of the feasibility of the proposed approach rather than as a definitive estimate of its predictive capability. Future work will focus on developing a complementary daytime classification model. Furthermore, we aim to integrate the nocturnal bed-band data with the other environmental and domotic sensors deployed across the facilities, moving toward a continuous 24-hour multimodal assessment framework.

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