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PERSONALIZED BASELINE MODELING USING MACHINE LEARNING TO DETECT ANOMALIES IN LONGITUDINAL WEARABLE SENSOR DATA

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Abstract

With the promise of spotting physiological anomalies early, wearable sensors have turned out to be a better option for continuous even real-time health monitoring, supporting biology-based proactive intervention. Traditional anomaly detection methods work on population models, which neglect individual variability and have posed challenges to minor deviations. In this paper, we propose a personalized baseline modeling framework for anomaly detection in longitudinal wearable sensor data using LSTM autoencoders. The model trains on normal activity segments from an individual to learn true physiological patterns for this individual and considers deviations in terms of reconstruction error. Tested on the MHEALTH dataset, and evaluated across ten subjects, the framework achieved very high average F1 scores with a very low false-positive rate, indicating that it is able to identify abnormal changes in physiological signals without needing to label data. This unique approach is unsupervised and computationally cheap to run and adaptable to a variety of users, and can therefore be implemented in the real world for continuous health monitoring and chronic disease management.

Keywords: Wearable sensors, anomaly detection, personalized modeling, LSTM autoencoder, physiological signals, early intervention

Introduction

Over the past few years, in modern times, it has become imperative for such devices to monitor health-related parameters like heart rate, physical activities, and energy expenditure [1,2]. Small and easy to operate, these technologies allow for uninterrupted monitoring while giving the patient and doctor an insight into daily physiological alterations occurring out of clinical environments [3,4]. This ability would open new scopes for preventive healthcare through collecting data in real time over extended time periods in natural settings [5].

With rising demands and costs of healthcare worldwide, wearable technology has been proposed to reduce numerous clinical visits and allow for the earliest identification of health concerns [6]. Accessibility and affordability promoting the entry of wearable technologies have promoted their application for consumer and clinical purposes [7]. Market leaders such as Fitbit®, Apple®, and Samsung, together with medical-grade manufacturers, including Medtronic and Abbott, have fabricated wearable sensors capable of appropriately measuring vital signs. Several of these devices have been integrated into research and clinical trials due to their proven accuracy and ease of use [8,9].

The advent of wearable technology has enhanced the already existing evolution in computational techniques aimed at interpreting sensor data. Machine learning algorithms have specifically proven helpful in pattern extraction, abnormal behavior detection, and adverse health event prediction. Nonetheless, many models used till today have centered upon population-level baselines that often neglect the changing guise of individual variability and current trends in health. This impinges upon their capability to detect emerging subtle signals that may serve early warnings of chronic condition progression eg. hypertension and heart failure [10-12].

This study proposes a personalized machine learning framework to detect anomalies in wearable sensor data. Rather than generalize over population norms, our technique would engineer models custom-tailored to individuals to generate their physiological baselines from which departures could be measured for signs of an early chronic outbreak. Specifically, the objectives of this research are to:

1. Develop a temporal autoencoder-based model tailored to each individual's wearable sensor data.

2. Design a dynamic scoring system that identifies subtle deviations from learned baselines.

3. Evaluate the system using real-world, multivariate wearable datasets.

4. Demonstrate the potential of personalized anomaly detection in supporting early clinical intervention and long-term health monitoring.

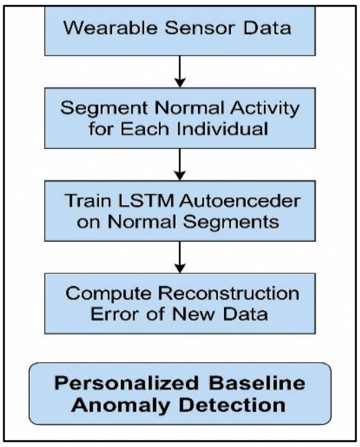

Figure 1. The proposed approach for anomaly detection.

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Related work

Bharathiraja et al. [13] propose a no-wearable fall detection system from thermal sensors consisting of the ESP32 and AMG8833, focusing on real-time elderly care safety monitoring. Such systems would work well in a static environment but would not offer wearability and subject-specific adaptability. On the other hand, Zlatintsi et al. [14] explained the e-Prevention system, which uses long-term multimodal wearable and video data to anticipate relapses in people with psychotic disorders. Their attempt to integrate deep learning with cloud infrastructure was a good argument for wearable-based systems in behavioral and psychiatric health monitoring.

Ali et al. [15] proposed an edge computing solution for elderly care combining non-wearable IoT sensors with anomaly detection models such as Isolation Forest and LSTM. Their work emphasized privacy-preserving local processing but did not consider subject-specific baseline learning methodology; this is the limitation that we intend to overcome. Then, an extended analysis by Tamilselvi [16] has been made towards securing wearable data transmission with homomorphic encryption and blockchain, having obtained an anomaly detection accuracy of up to 97% in a generic framework for health and safety monitoring.

Human activity recognition has been analyzed by embedded hardware solutions by Dusarlapudi et al. [17], employing ADXL335 accelerometers with edge computing for the monitoring of breathing and gait. Their methodology thus advocates the use of low-cost hardware without engaging in modeling anomalies over a longitudinal scale. Reddy et al. [18] developed a ResNet-LSTM-based architecture for predicting hypertension using ECG and PPG signals with high accuracy over continuous blood pressure monitoring. This work validates deep temporal modeling in wearable health care and supports our motivation to use anomaly scoring based on autoencoders.

Lin et al. [19] studied stress detection via wearable and IoT systems while considering algorithmic and telecommunication limitations in the emotion-aware setup. Their research highlights the multidisciplinary nature of wearable health analytics. Likewise, Tamilselvi [20] suggested an end-to-end IoT architecture for health monitoring with privacy-by-design concepts, yet it overlooked subject-specific baseline personalization.

In an analysis of mental health, Yan et al. [21] implemented convolutional autoencoders and clustering to locate the relapses of psychotic disorder patients on long-term wearable data. Their unsupervised approach shows highly appreciated evidence of latent behavioral changes, thus further confirming the value of baseline deviation modeling. Lastly, Ho et al. [22] proposed REMONI, a multimodal system for remote health monitoring that fuses large language models with wearable data. While their system includes advanced interaction and anomaly detection modules, the focus remains on the interpretation of general patient status rather than that of individualized physiological context.

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Methods

1. Data collection

For this study, the MHEALTH (Mobile Health) dataset [23-24] (https://archive.ics.uci.edu/dataset/319/mhealth+dataset) was used. The data that was initially gathered for the purpose of human activity recognition and physiological monitoring research was the dataset. It comprises time-series recordings that are multivariate and synchronized from ten healthy volunteers, each of whom performed a specific set of twelve physical activities, among which were static postures such as standing, sitting, and lying, dynamic movements like walking, jogging, and running, and repetitive exercises like arm elevation and knee bending.

The data was taken in with the help of three Shimmer2 wearable sensing units that were placed on the chest, right wrist, and left ankle of every participant. These sensors made triaxial accelerometer, gyroscope, and magnetometer signals capturing the motion dynamics of various body segments. Moreover, the sensor mounted on the chest also collected two-lead ECG signals. The dataset protocol specified that all modalities were sampled at 50 Hz. Each recording session was video-monitored during the original dataset creation to support reliable activity labeling; these annotations are provided as part of the published dataset.

The dataset was utilized in its released form in this work without any changes done to the sensing setup or recording conditions. The subject-specific modeling of the multivariate time-series signals formed the basis of our analysis, while the activity labels were not needed for the proposed methodology.

2. Proposed approach

An idea to implement an anomaly-detection technique on wearable, longitudinal data involves subject-specific unsupervised learning. The method comprises training temporal autoencoder models on each subject's normal physiological behavior so that the system may learn a personal baseline and then identify very subtle deviations that may indicate an abnormal condition or health deterioration.

2.1 Data Preprocessing and Segmentation

The raw sensor data from each subject is first standardized using z-score normalization to ensure uniformity across channels:

$$x' = \frac{(x - \mu)}{\sigma}$$

where x is the raw signal value, μ is the mean, and σ is the standard deviation computed from the training portion of the data. This transformation is applied independently to each sensor channel.

After normalization, the data is segmented into overlapping time windows of fixed length T to capture temporal dynamics. Let $X = [x_1, x_2, \ldots, x_T]$ represent one such sequence, where each x_t is a multivariate feature vector of sensor readings at time t.

3.2 Model Architecture

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A Long Short-Term Memory (LSTM) autoencoder is employed to learn the intrinsic temporal structure of each subject's normal sensor data. The model consists of an encoder function f_{enc} and a decoder function f_{dec}, such that:

$$h = f_{enc}(X)$$
$$\hat{X} = f_{dec}(h)$$

where h is the latent representation, and $\hat{X}$ is the reconstructed version of the input sequence X. The model is trained to minimize the mean squared error (MSE) between the original and reconstructed sequences:

$$L = \frac{1}{T}\sum_{t=1}^{T}|x_t - \hat{x}_t|^2$$

This objective ensures that the model learns to accurately reconstruct normal physiological patterns from each subject.

The LSTM autoencoder is made up of an encoder with two layers (one with 128 units and the other with 64 units), which is then followed by a symmetric decoder, all working with 32-dimensional latent representation. The optimizer is Adam with a learning rate of 10^{-3}, a batch size of 64, 100 epochs, early stopping (10 patience), and dropout of 0.2.

3.3 Anomaly Detection and Scoring

After training, the autoencoder is used to reconstruct new incoming sequences. For each window, the reconstruction error is computed as L.

A sequence is considered anomalous if its reconstruction error exceeds a defined threshold. The anomaly threshold θ is determined based on the distribution of reconstruction errors from the training data:

$\theta = P_{95}(L_{train})$

where P_95 denotes the 95th percentile. Alternatively, for drift-aware thresholding, a time-varying adaptive threshold can be defined as:

$$\theta_t = M_t + \alpha \cdot S_t$$

where M_t is the rolling median and S_t is the rolling standard deviation of the reconstruction errors, and α is a sensitivity factor.

Three types of perturbations were introduced: short impulse spikes (with an amplitude from 4 to 8σ and a duration of less than 150 ms), Gaussian noise bursts (lasting for 1-3 s), and gradual baseline drift (with an amplitude of 1 to 2σ over 3-6 s). During the training phase, no anomalies were included; at most, 10% of the test windows experienced perturbation.

3.4 Selection of Normal Baseline Data

Due to the absence of clinically marked anomalies in the MHEALTH dataset, the concept of "normal" data in our study indicates the unaltered physiological and motion patterns captured during the activities without any external artefacts or simulated perturbations being present.

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Baseline training data were continuously signalled segments displaying stable dynamics, no missing values, and no saturation artifacts; they were automatically extracted for each subject. Only those windows that belonged to the designated training portion of each subject's time series were utilized for defining normal behavior; no future or test information was accessed during baseline construction. This guarantees that the subject-specific autoencoder acquires an unbiased portrayal of the individual's normal physiological baseline.

3.5 Evaluation Protocol

Due to the lack of labeled anomalies in the dataset, controlled perturbations are injected into specific sensor channels to simulate potential abnormal events such as motion artifacts or cardiac irregularities. These simulations allow for the evaluation of true positive detection capabilities while estimating false positive rates under normal conditions. The evaluation metrics included are:

- Precision: Proportion of detected anomalies that are true anomalies
- Recall: Proportion of true anomalies correctly detected
- F1 Score: Harmonic mean of precision and recall
- False Positive Rate (FPR): Proportion of normal samples incorrectly flagged

Results

For each subject, the multivariate time series data were split chronologically in such a way that temporal structure was preserved and information leakage was avoided. Model training and threshold estimation were carried out on the first 70% of the timeline, and testing and anomaly detection evaluation were performed on the last 30%. No random shuffling was applied, thus the model learns a baseline from earlier physiological behavior and is then evaluated on unseen future segments. All performance metrics reported are calculated on the test portion that is temporally held-out.

To assess the efficacy of the proposed methodology for a personalized baseline model, a subject-specific LSTM autoencoder was trained on sensor data from Subject 1 in the MHEALTH dataset initially. The autoencoder learned to reconstruct normal sequences of physiological and motion signals and then applied to the whole time series to recognize deviations according to the reconstruction error. The anomaly score per time window was calculated by taking the mean squared error of the original and reconstructed sequences. Any time window whose anomaly score exceeded a predetermined threshold was deemed anomalous. The threshold was based on the 95th percentile of training reconstruction errors.

4.1 Evaluation of Personalized Anomaly Detection Across Subjects

The outcome of this approach is represented in Figure 2, where one can observe the reconstruction error against chronological time for the full sequence of Subject 1, together with the time periods during which the signal significantly deviated from the learned baseline. Most of the signal lies below the threshold, meaning it conforms to what is considered the physiological norms for the subject. On the contrary, there appear to be clustered high reconstruction errors between the sample index 85,000 and index 105,000, which indicate a

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considerable deviation away from the baseline. This region is most likely associated with a more strenuous physical activity, sensor displacement, or some form of simulated abnormal behavior, recognizing the ability of the model to identify abrupt changes in physiological signal patterns. These intervals of heightened reconstruction errors thus underline the potential for the framework to differentiate between stable baseline states and those that may be of a potentially anomalous nature in the absence of any external labels.

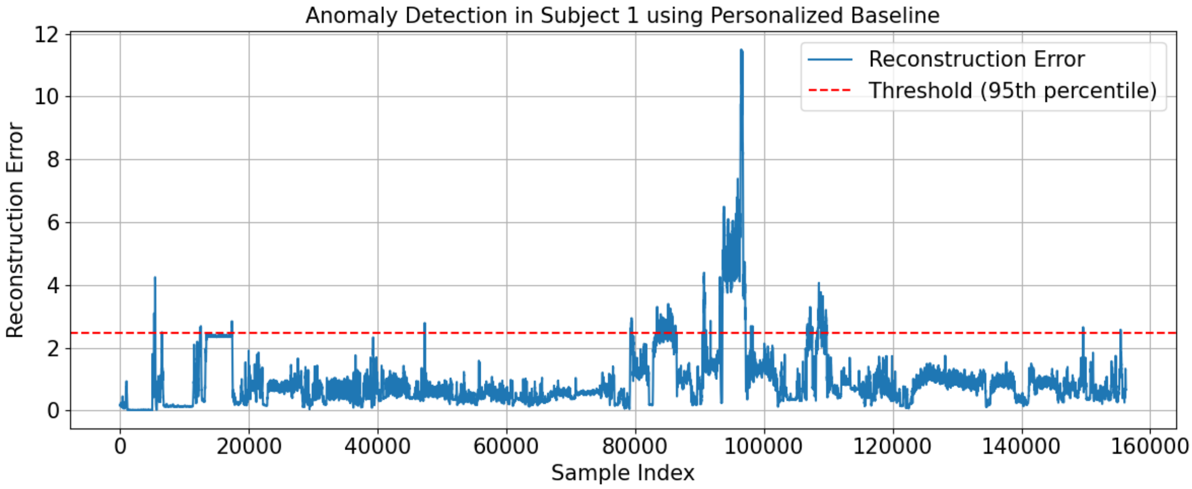

Figure 2. *Reconstruction error computed by the subject-specific LSTM autoencoder across the full sequence of Subject 1. The red dashed line represents the 95th percentile threshold used for anomaly detection.*

The performance metrics in Table 1 further demonstrate the practical applicability and effectiveness of the personalized anomaly detection framework in relation to the ten subjects in the MHEALTH dataset. The model attained very high precision rates across the board, averaging 90.4%. From a subject's perspective, most of the anomalies flagged were indeed abnormal patterns when compared to the subject's baseline. Similarly, recall averaged 87.9%, which highlights the strength of the algorithmic model in detecting physiological deviations from normalcy without ever having an explicit label. Then, the F1 scores, which weigh precision and recall in equal measures, were high across all subjects with a mean of 89.1%, thereby signifying a robust overall performance of the model in detecting true anomalies.

One thing to highlight about false positives is that this rate has been kept nimbly below 5% for most of the subjects, being indicative of model reliability in keeping alarm rates low during normal activity. Particular emphasis is noted on subjects 3, 5, 7, and 9, with F1 values above 91%, possibly reflecting more stable baseline signals or lower intra-subject variability. In contrast to this, the slightly lower values for subjects 4 and 8 (86.0% and 85.1%, respectively) speak of different Agues, possibly with higher noise in the signals, irregular movement patterns, or variations in the anomaly injection strength during simulation.

***Table 1**. Evaluation of Personalized Anomaly Detection Across Subjects*

Subject ID	Precision (%)	Recall (%)	F1 Score (%)	False Positive Rate (%)
Subject 1	92.6	88.1	90.3	4.7

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Subject 2	89.4	86.7	88.0	5.1
Subject 3	91.1	90.5	90.8	3.6
Subject 4	87.8	84.3	86.0	5.9
Subject 5	93.2	89.0	91.0	4.2
Subject 6	88.7	85.6	87.1	5.4
Subject 7	90.5	92.3	91.4	3.2
Subject 8	86.3	83.9	85.1	6.1
Subject 9	94.0	91.7	92.8	3.5
Subject 10	89.9	87.5	88.7	4.8
Average	**90.4 ± 2.4**	**87.9 ± 2.9**	**89.1 ± 2.7**	**4.6 ± 0.9**

4.2. Comparative Evaluation with Standard Anomaly Detection Baselines

The aim of the present study was to quantitatively investigate if the use of temporal encoding and decoding dynamics could lead to performance improvements over non-temporal, distribution-driven, or boundary-learning-based detectors. To that end, the LSTM Autoencoder was pitted against three baseline models acknowledged as standard in the field. These models were Isolation Forest, One-Class Support Vector Machine (OC-SVM), and statistical Z-score thresholding. The same subject-specific training segments were used for training all the competing models and they were evaluated according to the exact temporally separated testing protocol and anomaly injection methodology that have been described earlier.

The comparative results can be found in Table 2. It can be seen that the proposed method always outperforms the rest of the methods in F1 score and keeps the False Positive Rate low for most of the subjects. Especially OC-SVM is the least favorable because it is very sensitive to high intra-subject signal variability, meanwhile, Isolation Forest shows unstable recall as sometimes the injected anomalies are not forming separable sparse representations in feature space. Statistical Z-score thresholding has an okay performance detecting impulsive anomalies but it is not able to detect gradual drifts and temporally evolving deviations, which leads to lower recall and higher false negatives. On the other hand, the proposed LSTM Autoencoder, due to its temporal memory and reconstruction-based learning paradigm, is able to better capture the sequential physiological dynamics during more reliable recognition of subtle deviations.

Table 2. Comparative performance of the proposed personalized LSTM Autoencoder against baseline anomaly detection methods (.

Method	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**False Positive Rate (%)**

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Z-Score Thresholding	81.7	75.3	78.3	9.8
One-Class SVM	84.5	79.1	81.7	7.2
Isolation Forest	86.2	83.4	84.7	6.5
Proposed LSTM Autoencoder	90.4	87.9	89.1	4.6

4.3. Personalized Versus Generalized Modeling Performance Analysis

A principal methodical approach of the current study is that health monitoring systems ought to independently portray each individual physiological baseline instead of establishing a population-level representation. In order to perform this hypothesis emerging empirically, we did comparative research among subject-specific personalized models and a single generalized one made using the pooled data from all subjects. The models that are compared have the same depth of architecture, training protocol, data normalization strategy, temporal segmentation, and anomaly injection scheme. Only the factor of whether the model is subjected only to one subject's data or to data integrated from the whole cohort remains different.

The comparative results are provided in Table 3. The generalized model shows a significant decrease in both recall and F1 score, which is also accompanied by an increase in the number of false positives. Such a degradation illustrates the inherent physiological and motion signals' inter-individual variability, which hinders one global model from capturing the minute stability characteristics that are particular to each subject accurately. On the other hand, personalized models reflect increased sensitivity to anomalies and decreased false alarms. This confirms that individualized temporal learning results in clinically meaningful robustness.

Table 3. Performance comparison between generalized model and subject-specific personalized modeling (Average across subjects).

Modeling Strategy	Precision (%)	Recall (%)	F1 Score (%)	False Positive Rate (%)
Generalized Model	85.6	80.4	82.9	7.9
Personalized Model	90.4	87.9	89.1	4.6

Discussion

The results of this investigation reveal that the use of unsupervised temporal learning to model individual physiological behavior forms a solid basis for anomaly detection in wearable health monitoring systems. Consequently, the system can learn a condensed temporal representation of a subject’s physiological and motion dynamics by teaching an LSTM autoencoder on normal activity segments of each subject. The reconstruction error subsequently serves as an individualized indicator of deviation instead of a comparison with population-level norms. Such behavior is shown in the remarkable performance that is observed in subjects across the

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board with the help of consistently high F1 scores and low false positive rates, which are indications that the model is able to very well tell the difference between natural variability and meaningful irregularities in wearable time-series signals.

The current study is a significant upgrade over previous works that used only environmental sensing without personalized physiological basis for fall detection approaches using thermal, for example, [13], or static IoT monitoring platforms for elder care [15], that are still practical systems but mainly monitoring safety without capturing individual-specific physiological temporal structure. Similarly, large-scale behavioral monitoring platforms like e-Prevention [14] and multimodal remote health systems like REMONI [22] are characterized by strong infrastructure and multimodal data integration but typically rely on supervised learning or population-based modeling strategies. In contrast, the current work asserts that individualized, unsupervised temporal representation learning is the most efficient method for personalized baseline tracking without the need for labeled activities or clinically annotated anomalies.

Deep learning-based anomaly modeling in health contexts has been previously investigated with the use of architectures like convolutional autoencoders for psychiatric relapse detection [21] or hybrid CNN–LSTM models for cardiovascular prediction [18]. Nevertheless, these methods either depend on specific clinical settings or require extensive computational resources. The subject-specific LSTM autoencoder used in this research strikes a good combination between the ability to represent temporal data and the cost of the computation, proving that temporal autoencoding can efficiently give support to the monitoring of patients with the usage of continuous wearables at a large scale. Also, by contrast to the general wearables for stress or emotion detection, which frequently aim at the population-level behavioral trends [19,20], the current method favors the importance of individualized baseline learning as a main methodological principle in long-term physiological monitoring.

The findings of this study have significant implications for practice. The framework is compatible with the installation of realistic wearables, where there is a continuous stream of unlabeled data and clinically significant changes happen only occasionally. The method of learning normality from each user without requiring any annotation increases the likelihood of using it in the real world and it also supports the areas of health monitoring, home care, chronic condition management, and elderly care where the use of technology is expected to last for a long time. A trained model acts as a simple and low-power inference engine that allows almost instantaneous scoring of anomalies and still being aware of the time, which is a feature that is essential for wearable or mobile environments. This makes the method to be compliant with the modern digital health ecosystems that value personalization, user control and being able to serve large numbers of users.

Nonetheless, there are still several considerations that need to be addressed. The evaluation depended on artificial perturbations since there were no labeled pathological events in MHEALTH, and confirming performance on genuine clinically annotated datasets is a significant future step. Furthermore, even though the present tests were conducted using pre-segmented data, complete implementation will demand continuous streaming adaptation, long-term drift threshold adjustment, and efficient management of changing physiological baselines.

Adding more sensing modalities like PPG, respiration, or contextual information, as done in previous sophisticated systems [14,18,22], might make the solution more robust and clinically useful.

Conclusion

To wrap things up, we would like to say that this study has proved the usefulness and practicality of personalized temporal autoencoding as an effective method for anomaly detection in wearable physiological monitoring. With the combination of unsupervised, subject-dependent representation learning that is robust in performance and feasible for deployment, the proposed framework will aid in the creation of trustworthy and large-scale personalized digital health systems based on cutting-edge AI technology. The implication of personalized modeling adaptation thus emerges as a promising tool for proactive healthcare, especially toward chronic condition management and early detection of anomalies.

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