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Modelling of an intelligent biosurveillance system based on electronic sensors, big data and statistical analysis for the prediction of variations in biological parameters

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ABSTRACT

Modern biosurveillance benefits from the convergence of biology, electronics, the Internet of Things, big data, statistical analysis and artificial intelligence. Wearable sensors and biosensors can generate continuous time series describing various physiological or biochemical parameters. However, the scientific value of these measurements depends on the quality of the sensors, signal processing, the ability to manage large data flows and the use of appropriate statistical methods.

This article proposes the modelling of an intelligent biosurveillance system based on an integrated chain ranging from the electronic acquisition of biological parameters to the prediction of their variations. The model combines sensors,

signal conditioning, a microcontroller, IoT communication, Big Data infrastructure, pre-processing, multivariate statistical analysis and predictive models.

The proposed methodology is quantitative, longitudinal, analytical and predictive. It involves assessing sensor reliability, conducting descriptive and correlational analyses of signals, analysing time series, and comparing several machine learning and deep learning algorithms. Particular attention is paid to data quality, artefacts, inter-individual variability, confidentiality and the cautious interpretation of algorithmic outputs.

Keywords: Biomonitoring; biosensors; electronics; Big Data; statistical analysis; biological parameters; time series; machine learning; IoT; prediction.

1. Introduction

1.1. Scientific context

Biological monitoring has long relied on one-off measurements carried out in the laboratory or in s using specialised equipment. The rise of miniaturised electronics and wearable devices now makes it possible to envisage the continuous collection of numerous signals, paving the way for a more dynamic representation of biological variations.

Recent systems combine physiological, bioelectrical, optical or electrochemical sensors with digital circuits capable of conditioning, converting and transmitting signals. Research carried out between 2024 and 2026 on wearable biosensors emphasises miniaturisation, flexibility, non-invasive measurement, integration with the IoT and the increasing use of artificial intelligence models.

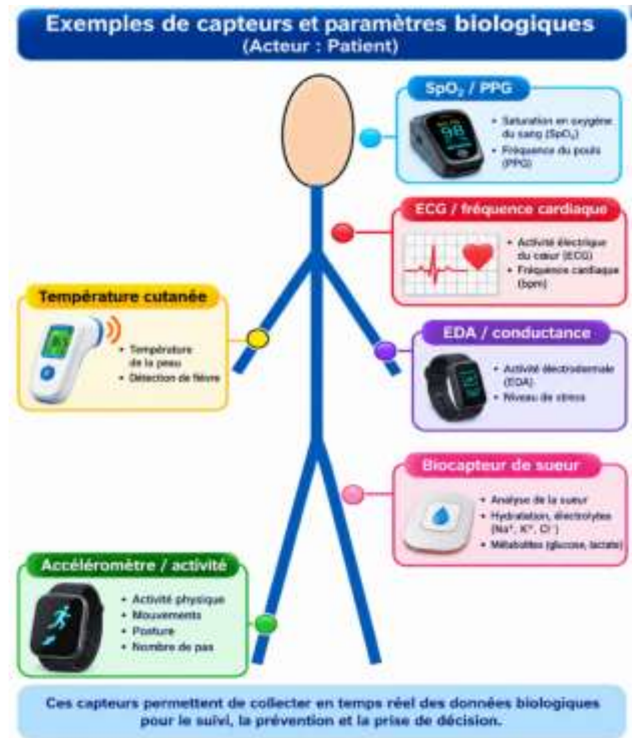

Figure 1. Examples of sensors and biological parameters.

1.2. Research question

The availability of sensors alone is not sufficient to build a scientific biomonitoring system. Biological data are noisy, heterogeneous, highly time-dependent and context-sensitive. An observed variation may result from a genuine physiological phenomenon, movement, a loss of contact, a change in temperature or a transmission error.

Main question: How can an intelligent biosurveillance system be modelled, integrating electronic sensors, Big Data and statistical analysis, in order to collect, process, characterise and predict variations in biological parameters?

Which biological parameters are the most relevant and measurable?

Which sensors and circuits ensure that the data acquired is usable?

How should the ingestion and storage of data streams be organised?

Which statistical methods distinguish between normal and atypical variations?

Which predictive models can forecast trends over time?

How can the reliability and generalisability of the system be measured?

2. Objectives of the study

2.1. General objective

To model an intelligent biosurveillance system based on electronic sensors, a Big Data infrastructure and statistical analysis for the study and prediction of variations in biological parameters.

2.2. Specific objectives

To identify measurable biological parameters.

To select detection technologies.

Define an electronic data acquisition architecture.

Design the Big Data architecture.

Define the pre-processing steps.

Apply appropriate statistical analyses.

Compare several predictive models.

Assess performance and reliability.

Identify ethical and confidentiality constraints.

3. Literature review

3.1. Biosensors and wearable technologies

Wearable biosensors convert a biological or physicochemical phenomenon into a measurable signal. Recent publications describe systems capable of monitoring heart rate, temperature, oxygen saturation, electrodermal activity and certain biomarkers present in body fluids.

3.2. Big Data and biological data

Continuous biological data combines volume, velocity, variety, issues of veracity and the search for value. A distributed architecture facilitates continuous ingestion, the storage of long time series and parallel analysis.

3.3. Statistical analysis and prediction

Statistical analysis enables us to describe distributions, measure variability and quantify uncertainty. Machine learning complements this approach by classifying states, detecting anomalies and predicting changes in variables.

Table 1. Summary of recent research.

Reference	Field	Contribution	Main challenge
Kazanskiy et al., 2024	Flexible wearables	Non-invasive monitoring	Stability and accuracy
Anbuselvam et al., 2024	Cardiovascular	Continuous monitoring	Artifacts and validation
Fan et al., 2025	Bioelectronics	High-fidelity interfaces	Cost and manufacturing
Tu et al., 2025	Biomolecular	Longitudinal data	Standardisation
Min et al., 2025	Pressure & ML	Algorithmic estimation	Calibration
Güntner et al., 2026	Metabolism	Molecular sensors	Interpretation

4. Biological dimension

The choice of parameters must be based on biological justification and on the feasibility of data acquisition.

Table 2. Biological parameters and detection technologies.

Parameter	Interpretation	Unit	Technology
Heart rate	Cardiovascular activity	bpm	PPG / ECG
SpO_2	Peripheral oxygenation	%	Red/IR optics
Temperature	Thermal status	°C	Thermistor

Breathing	Respiratory activity	cycles/min	Impedance / PPG
ECG	Cardiac electrical activity	mV	Electrodes
EDA	Skin conductance	µS	Electrodes
Activity	Movement	m/s²	Accelerometer

5. Electronic components

The electronic chain comprises the sensor, amplification, filtering, analogue-to-digital conversion, the microcontroller and communication. A measured signal can be represented by $X(t)=S(t)+N(t)$, where $S(t)$ is the useful signal and $N(t)$ is the noise.

Sensitivity and resolution.

Sampling frequency.

Power consumption.

Biocompatibility and comfort.

Stability and calibration.

Compatibility with communication protocols.

6. Big data architecture

The volume of observations can be approximated by $N=P\times C\times F\times T$, where P represents the participants, C the channels, F the acquisition frequency and T the duration.

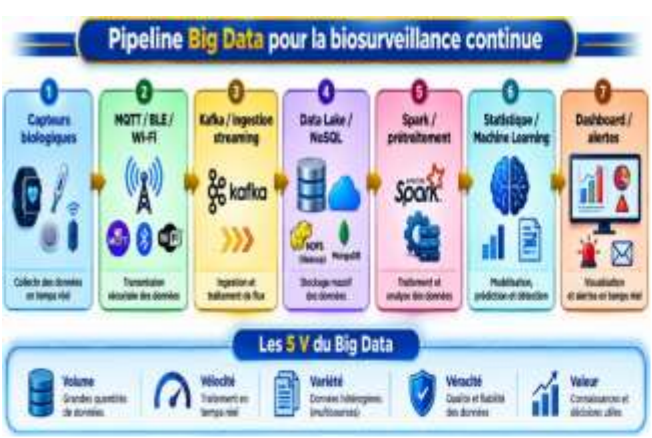

Figure 2. Proposed Big Data pipeline.

7. Data structure and governance

Table 3. Logical data structure.

Field	Description	Example
subject_id	Pseudonymised identifier	S001
Timestamp	Timestamp	2026-08-20 10:15:04
heart_rate	Heart rate	78
spo2	Oxygen saturation	98
Temperature	Temperature	36.7
Activity	Context	walking
signal_quality	Signal quality	0.94
sensor_id	Source	PPG_02

8. Pre-processing

Pre-processing includes the detection of missing values, noise filtering, artefact correction, temporal synchronisation, normalisation and window segmentation.

Document any imputation;

Use signal quality to filter out artefacts;

Align data streams to a common clock;

Avoid transformations that introduce information leakage.

9. Statistical analysis

9.1. Descriptive statistics

The mean, median, standard deviation, quantiles and coefficient of variation will be used to characterise the distributions.

9.2. Correlation

Pearson's correlation can be used when its assumptions are met; Spearman's correlation is useful for non-normal distributions or monotonic relationships. Correlation does not imply causation.

9.3. Multivariate analysis

Analyses can incorporate several parameters simultaneously using regression, principal component analysis or mixed models, depending on the experimental design.

10. Time series and forecasting

A biological time series can be expressed as Yt = f(Yt-1, Yt-2, ..., Xt) + εt. Possible approaches include ARIMA, state models, LSTM, GRU and temporal Transformers.

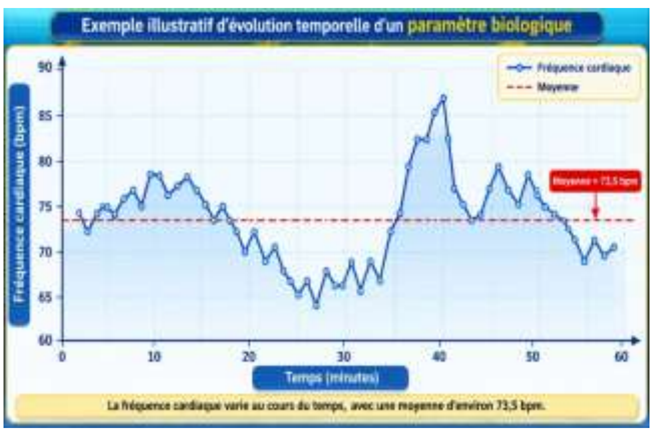

Figure 3. Illustrative time series (simulated data).

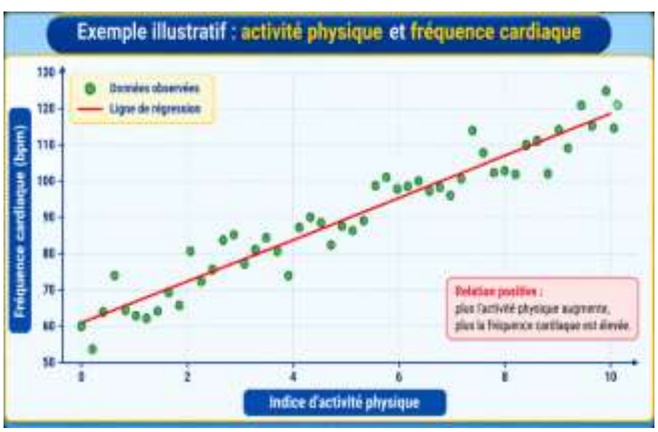

Figure 4. Illustrative correlation between activity and heart rate (simulated data).

11. Proposed conceptual model

Figure 5. Proposed conceptual model.

The quality of the sensors influences the quality of the data, which in turn determines statistical robustness and predictive performance. Contextual variables can reduce false alarms.

12. Methodology

12.1. Type of study

A quantitative, longitudinal, experimental and predictive approach, preceded by a pilot phase.

12.2. Population

For human application, the population and inclusion criteria must be explicitly defined and subject to appropriate ethical validation.

12.3. Experimental design

Table 4. Proposed experimental design.

Phase	Stage	Objective
1	Calibration	Compare the sensors against a reference
2	Test	Test stability and quality
3	Data collection	Recording the series
4	Pre-processing	Clean and synchronise

5	Analysis	Describe and model
6	Training	Training the models
7	Validation	Evaluate using independent data

13. Variables and operationalisation

Table 5. Key variables.

Variable	Role	Measure
Signal quality	Moderator	SNR / artefact rate
Heart rate	Target	bpm
SpO_2	Target	%
Temperature	Target	°C
Activity	Contextual	Index/category
Time	Structural	Timestamp
Anomaly	Binary target	0/1
Performance	Result	MAE/RMSE/F1/AUC

14. Model evaluation

For regression, the study may use MAE, RMSE and R^2. For classification or supervised detection, it may use Accuracy, Precision, Recall, F1-score, sensitivity, specificity and AUC. The separation into training, validation and test sets must follow the chronological order to avoid information leakage.

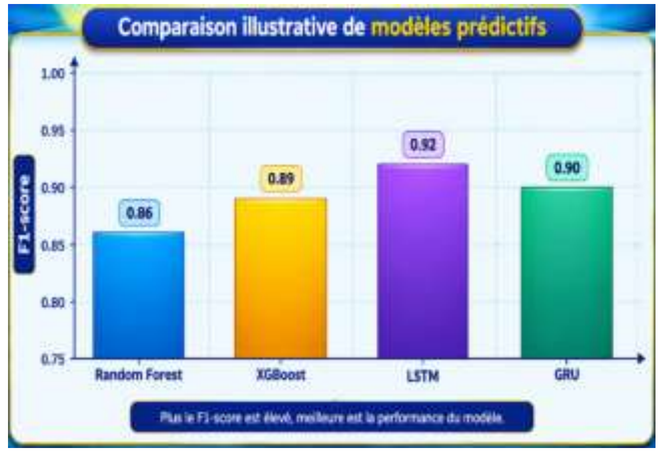

Figure 6. Illustrative comparison of models (simulated values).

15. Expected results

Continuous and documented data collection;

Detection of signal quality issues;

Characterisation of trends and correlations;

Identification of atypical variations;

Objective comparison of models;

Production of interpretable dashboards.

16. Discussion

The value of this approach lies in the integration of disciplines: biology defines what is being measured, electronics determines the reliability of data acquisition, Big Data organises data flows, statistics quantify variations, and AI supports prediction.

Distinguishing between biological variation and instrumental variation is a key challenge. Any alert must be accompanied by information on signal quality and context.

17. Ethical considerations and safety

Informed consent;

Pseudonymisation;

Encryption and access control;

Traceability of processing;

Right to withdraw consent;

Ethical approval;

Do not present a prediction as an automatic clinical diagnosis.

18. Limitations

Inter-individual variability;

Motion artefacts;

Sensor drift;

Missing data;

Need for sufficient volume;

Risk of overfitting;

Energy autonomy;

Confidentiality of biological data.

19. Outlook

Future developments include flexible electronics, molecular sensors, Edge AI, federated learning, explainable AI, multimodal models, temporal Transformers and biological digital twins.

20. Conclusion

The proposed system links the organism, sensors, electronics, networks, big data infrastructure, statistical analysis and predictive models. Its quality depends on the robustness of the entire chain rather than on any single algorithm.

This architecture provides a scientific basis for a future multidisciplinary prototype, adaptable to different biological, environmental or experimental contexts.

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