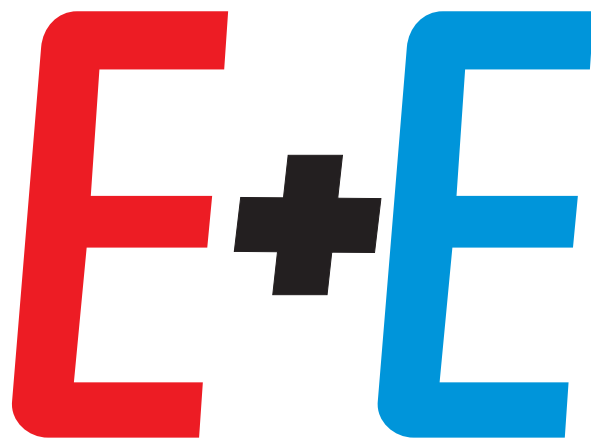


1-2 • 2026

**ЕЛЕКТРОТЕХНИКА
И ЕЛЕКТРОНИКА**

**ELECTROTECHNICA
& ELECTRONICA**



PUBLISHED BY

CEEC – THE BULGARIAN UNION OF ELECTRONICS, ELECTRICAL ENGINEERING AND TELECOMMUNICATIONS
MEMBER OF

FNTS – THE BULGARIAN FEDERATION OF THE SCIENTIFIC ENGINEERING UNIONS



ELECTROTECHNICA & ELECTRONICA E+E

Vol. 61. No 1-2/2026

Quarterly scientific and technical journal

Published by:

The Union of Electronics, Electrical Engineering and Telecommunications /CEEC/, BULGARIA

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ISSN 0861-4717

eISSN 2603-5421 Online

C O N T E N T S

Stanislav Ivanov

Volumetric Visualization of Spatial Radio Link Performance for Anomaly Monitoring and Weather-Related Attenuation in Modern Mobile Networks

1

Ertan M. Geldiev

A Multi-Model Consensus Framework for Pneumonia Detection: Optimizing Diagnostic Sensitivity under "Green AI" Constraints

8

Vanessa S. Nazakova

Design and Hardware Optimization of a Modular EEG Acquisition System for BCI Applications

19

Takeshi Tanaka, Tomoo Sigehuzi, Masayuki Yamauchi, Shuji Oji, Masaya Watanabe, Satoru Tada, Koji Kakugawa, Katia Vutova

IoT-based indoor environmental monitoring and CO₂ prediction using FIWARE and Sigfox for smart laboratory environments

28

Volumetric visualization of spatial radio link performance for anomaly monitoring and weather-related attenuation in modern mobile networks

Stanislav Ivanov

Modern cellular networks lack a unified, vendor-independent mechanism for observing radio-link performance directly at the end-user segment of the Uu interface, where the combined effects of propagation conditions, cell load, and environmental factors are ultimately experienced. The prototype system presented in this work addresses this gap by continuously monitoring key downlink radio metrics – RSRP and RSRQ – directly from the client devices and correlating them with the serving cell in real time. Unlike traditional network-side counters, this approach captures impairments that cannot be reliably inferred from centralized base-station statistics alone, including weather-induced attenuation like rain, and user-specific degradation.

Atmospheric conditions can be correlated with degrading signal performance, for instance ITU-R P.838-3 specifically addresses the effects of rain on the signal quality and power. By integrating volumetric visualization of rain-related signal attenuation with live radio measurements, and data points from end user devices, following standards like ITU-R P.838-3, the system provides immediate spatial context for performance anomalies that would otherwise require manual labor across multiple systems.

Keywords – monitoring, weather, performance, end-user, visualization

Обемна визуализация на производителност на радиовръзките, мониторинг на аномалии и метеорологично затихване в съвременните мобилни мрежи (Станислав Иванов). Съвременните клетъчни мрежи не разполагат с единен, независим от производителя механизъм за наблюдение на производителността на радиовръзката директно в потребителския сегмент на Uu-интерфейса – където често се изпитва ефекта от натоварената мрежа и моментните условия на заобикалящата среда. Разработената прототипна софтуерна система измерва качеството на услугите в една телекомуникационната мрежа, като следи RSRP и RSRQ индикаторите на ниво крайно потребителско устройство, в комбинация с данни от обслужващата базова станция в реално време. За разлика от традиционните мрежови индикатори за следене на качеството на една телекомуникационна мрежа, този подход успешно измерва ефективната деградация на услугите, които трудно биха се измерили едностранно от страна на базовата станция. В това число влизат и измервания на атмосферните условия и техният ефект върху получения сигнал, както и такива поради качеството на клиентското оборудване.

Съществува връзка между атмосферните условия и деградацията на радиосигнала. Стандарт ITU-R P.838-3 разглежда конкретно ефектът на валежите върху качеството и мощността на сигнала. Системата интегрира модела описан в стандарта, като корелира информация за атмосферните условия на дадена точка, с измервания на качеството на радиосигнала в реално време, както и метаданни от клиентските устройства. Платформата предоставя възможност за навременното диагностициране на аномалии в производителността на една мрежа – нещо, което днес налага ръчната обработка на данни от няколко системи.

This work examines two distinct functional capabilities for monitoring end-user radio link between user equipment (UE) and its serving cell within a cellular network. The first capability, radio performance monitoring, provides direct, real-time visibility into radio-link quality as experienced at the device level. The second enables spatial interpretation of existing atmospheric conditions influencing signal propagation. Together, these functions support centralized operational monitoring and engineering analysis by exposing conditions on the *Uu interface* that are not readily observable through conventional network-side metrics alone.

A software prototype system was designed and developed that unifies those capabilities, supporting the process of radio link performance monitoring, from the point of view of the UE device.

Work in the field of radio link and wave measurements is nothing new. A paper [9] was published in 2024 that is an empirical field-measurement study of a commercial 5G Non-Standalone network. The paper dealt with how much downlink performance can a real commercial 5G NSA deployment deliver, and how can variations in that performance be explained. The conclusion was that 5G NSA can deliver close to 1Gbit/s thus substantially outperform LTE, but throughput remains highly dependent on line of sight, modulation and rate adaptation.

4G networks and measurements for the same were also studied [10] which is an applied 4G LTE radio-network planning and optimization analysis. The authors combined conventional link-budget and propagation model calculations, with a real drive test (Tiarret, Algeria), and before-and-after comparison of LTE radio KPIs following what they call network “treatment” or optimization. The basic engineering loop established was: Measure the network; Identify weak coverage and interference areas; Modify the radio network; Repeat the drive test; Check whether QoS has improved. This operational optimization loop is considered one of the key deliverables of the paper.

While this work is beneficial for the industry and the adoption of 5G, it keeps the focus on the process of measuring signal behavior, and quality, in certain conditions. The prototype system is aiming to establish a causal link between end user experience, weather conditions and the servicing telecom infrastructure, based on already established and standardized measurement techniques.

Data source

Data is collected from multiple independent sources and aligned into a unified, time-indexed data point. Only through normalization and correlation of these heterogeneous datasets can a coherent view of radio-link conditions be obtained. This approach inherently depends on the availability and near-real-time delivery of all contributing data sources. Consequently, data quality becomes critical, as partial or missing inputs can invalidate an entire data point.

The user equipment (UE) plays a **central role by providing the primary dimensions of the data** for both radio link performance assessment and weather-related attenuation analysis. In addition to *device metadata*, the UE computes *Reference Signal Received Power (RSRP)* and *Reference Signal Received Quality (RSRQ)* through its on-board radio electronics. Together, these metrics provide a reliable identification of downlink signal strength, quality, and stability, as experienced at the receiver. Additional UE-provided information, including device metadata and geospatial coordinates, further enable precise spatial contextualization of measurements and support map-based correlation.

To form the complete path between the UE and the serving cell, **additional data feed is taken**, based on the context from the UE metadata. Resolving the connected cell to its geospatial coordinates is the next critical bit, since that gets linked to the UE.

Once both the UE and the cell are correlated, the data requires an additional **dimension to form a valid 3D volumetric representation**, for what we are trying to achieve. This is done by cross-feeding weather-related data, e.g. precipitation. The final shape takes place by unifying and displaying all these data sets in a single visual scenario, as depicted below.

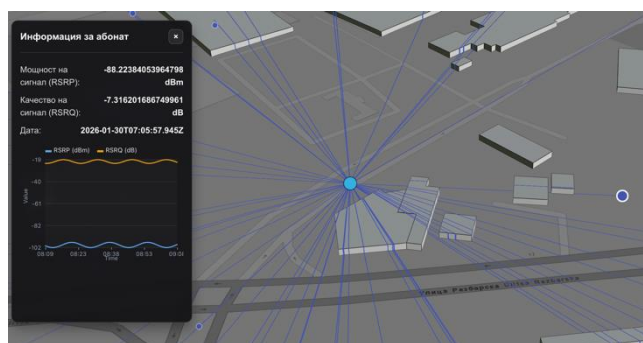


Fig.1. Rendering of UE (right) – Cell (center) relation.

Reliability of reference indicators

Both RSRP and RSRQ are standardized by 3GPP – LTE (4G) *TS 36.214* (Physical layer) [5], 36.133 (UE) [6] and NR (5G) *TS 38.215* (Physical layer) [7], 38.133 (UE). The specifications are exact mathematical definitions, measurement bandwidths, filtering (L1/L3), reporting ranges and quantization, as well as accuracy requirements per UE category.

RSRP is measured in *dBm* or *decibel-to-1-milliwatt* – the average received power of one reference *resource element* (RE) from a cell. The typical range being from -140dBm (weak) to -44dBm (excellent, i.e. better connectivity for the UE). Since RSRP is not total signal power, and is normalized to a single RE, this makes it comparable across bandwidths.

RSRQ is dimensionless (no physical unit) quality metric that relates RSRP reference RE power to total received power (RSSI), measured in dB or decibels.

$$(1) \quad RSRQ = \frac{N \times RSRP}{RSSI}$$

Where N is the number of resource blocks, $RSSI$ is the total received wideband power that includes signal, interference and noise.

The typical range of RSRQ is from -19dB (weak) to -3dB (excellent). Unlike RSRP however, RSRQ captures interference and load. Below table lists the various threshold levels widely accepted by vendors, although not standardized.

Level	RSRP	RSRQ
Excellent	≥ -80	≥ -10
Good	from -80 to -90	from -10 to -15
Medium	from -90 to -100	from -15 to -20
Low	≤ -100	< -20

Table 1. Vendor recognized levels of reference signals.

In LTE and NR systems, reference signals are an integral part of the air interface and are transmitted continuously within the orthogonal resource structure of the serving cell radio signal.

The UE can isolate the desired reference signal from interference and noise, allowing independent measurement of signal power, interference levels, and resource utilization. In contrast, second- and third-generation networks primarily relied on composite received power measurements, where signal, interference, and noise were not distinctly separable. By introducing OFDMA and subcarrier-level transmission, fourth- and fifth-generation mobile networks substantially improved the accuracy and reliability of radio signal quality measurements reported by user equipment.

Reference measurement

UE devices cannot replace professional equipment in terms of data accuracy for measuring reference signal quality and power. While it is true that measurements are less accurate, the provided metrics of RSRP and RSRQ are standardized and reliable-enough to reach a conclusion to the quality of the user connection, and whether they (users) are impacted by it. This scenario is nothing new, with work in the field already being done in the past.

A 2016 paper by the University of Aalborg, Denmark, investigated how consumer grade Android smartphones compare to professional Radio network scanners for RSCP (3G) and RSRP (LTE) [1]. *NetMap* software was used on Google Nexus Android phones, and its results compared to phones connected to passive Radio network scanners. The scanner was configured with the best resolution and sampling time.

Scenario	RMSE (scanner)	RMSE (phone)
Indoor	3.0 dB	2.1 dB
Outdoor	3.0 dB	0.8 dB
City center	5.8 dB	1.9 dB
Highway	7.3 dB	1.8 dB
Average	4.7 dB	1.7 dB

Table 2. Simplified RSRP results table (scanner vs phone).

The Root Mean Square Error (RMSE) is expressed as:

$$(2) \quad RMSE(x, y) = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2} \quad [dB]$$

Where x_i = RSRP reported by the phone, y_i = RSRP measured by the scanner device and N is the number of synchronized samples. RMSE is an absolute error metric, expressed in dB, that shows how far apart are the phone's RSRP values from the scanners.

The study concluded, that when comparing LTE RSRP measurements, the RMSE between a crowdsourcing smartphone application and a professional tool running on the same handset is approximately 2 dB across environments, indicating high measurement accuracy.

Centralized monitoring platform

The system is created from the ground up, leveraging open frameworks. The key ideology of the platform is correlating the various data sources as one user-centric view, rather than a disconnected set of data layers (what many software systems choose to do).

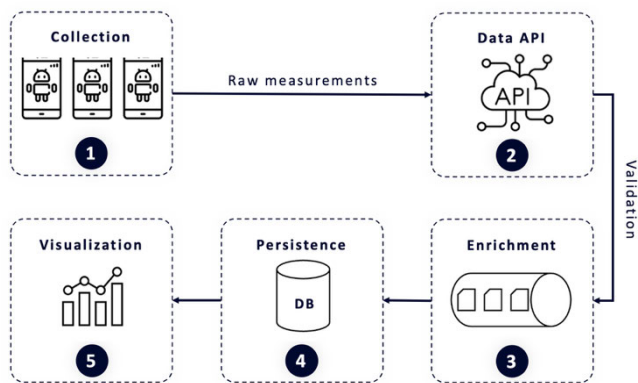


Fig.2. Cell – UE connection and details

To make this work the Figure 2 architecture was realized. Relying on industry standard radio metrics was critical, which is why RSRP and RSRQ were selected, offering a common view across vendors and even generations of equipment. The (1) Collection layer is responsible for gathering and relaying of the raw measurements to the (2) API. This is where various data sources are reviewed and correlated, so a more complete picture is painted. A radio measurement data point makes more sense when combined with the UE's geospatial data, and the location of the cell. Validation and Enrichment (3) is a critical process, which guarantees data is reliable, and there are no missing attributes. At this stage the data is correlated and ready to be (4) persisted (*work done in the field of specialized databases for spectrum management research of electromagnetic fields created by a wide range of devices and systems [4] was technically inspirational for identifying the key challenges a multi-dimensional metric system would have today*), which makes it available to (5) display in the web user interface. Storing data in an efficient and performing way is essential for such a system.

Unifying data from different sources brings its own unique set of challenges. One of the key moments this platform is addressing is the correct resolution and visualization of the interaction between the UE and the serving cell (Uu interface). In all studied cases, the UE devices (especially commercial ones) do not provide sufficient information for resolving cell information. Which is why we require correlation of multiple data sources, to be able to complete the full story.

Coming to the web user component and how data is visualized, each active Cell is rendered with the minimum available metadata – cell identifier, operator, number of active UEs, bandwidth, and EARFCN.

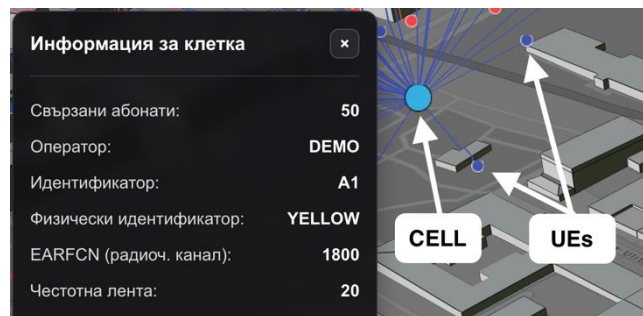


Fig.3. Cell – UE connection and details

The cell object is a larger circle, compared to the UEs it serves – each depicted by a smaller one. A straight line represents the active Uu radio interface, established between the cell and the UE. A line does not represent the physical characteristics of the radio signal but is used to show that an active connection is in process. Both the cell and the UE circles are available for selection, which then brings up a context menu of details about the selected object.

When a UE is selected, this brings up its own measured RSRP and RSRQ values – the last reported value and a brief historical timeseries depiction of the same (up to 1 hour, as seen on figure 4).

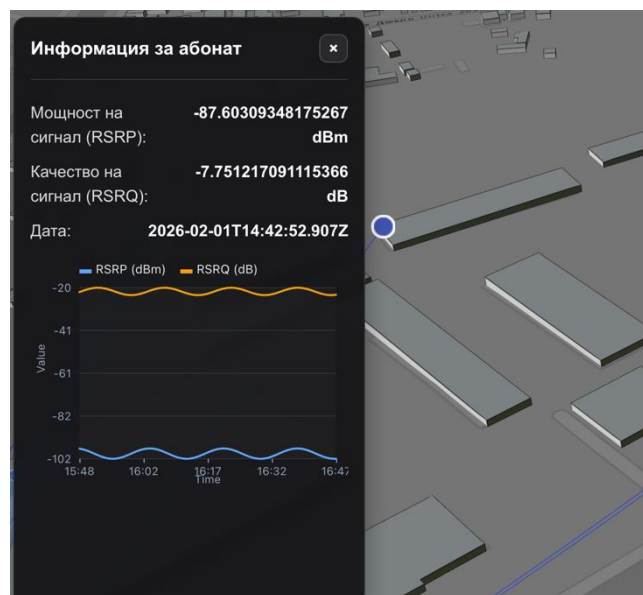


Fig.4. Cell – UE reported values and details

Each data point on the timeseries is one reported measurement sent by the end device. The data is presented raw i.e. there is no aggregation, since the depicted historical period is short and we are interested in data precision.

A web user can interact with the live map, by exploring the available filters to narrow down problematic UEs and their serving cells in free floating mode. The immediate benefit of this perspective is speed, when it comes to analyzing more busy areas or cells, subject to peak traffic.

The diagnostic area of the interface allows the user to activate various algorithms that analyze the available data for painting different perspectives. Data can be evaluated for wrongfully connected UEs, which can be caused by mis-configured serving cells and their thresholds, as seen on *Figure 5*.

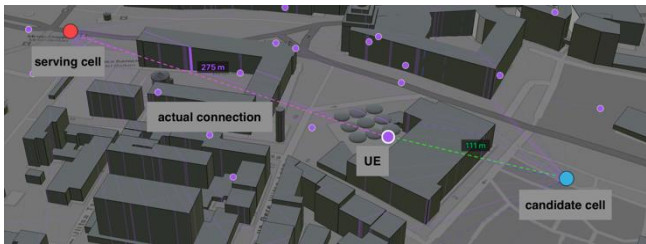


Fig.5. Auto-detecting anomaly connections in a network.

The system can automatically detect UEs connected to the wrong cell, based on environment parameters such as distance. If an active cell exists within range, closer to the currently serving one for the UE, the system will flag this as an anomaly. This is done by measuring the distance between the UE and the serving cell and then looking for cells in closer proximity on the map from the same operator (the figure shows the UE is 111 meters away from a prospect cell, while it is 275 meters away from its currently serving one). One can argue distance should not be the only factor for deciding what is an anomaly – for instance, obstructions can easily make the prospect cell connection signal weaker and therefore explain why a more distant cell is used. The algorithm allows to be extended with additional dimensions of data for a more comprehensive decision-making process. For one, information from the cell's configuration pane can be integrated to make the anomaly detection more robust and precise.

A similar perspective is shown on a busier area, Figure 6, where closely positioned and mis-configured cells can create an overlap area with strong signals from both – creating an opportunity for smaller mistakes in the configuration to lead to the UEs connecting to a more distant cell.



Fig.6. Spotting wrongfully connected UEs.

RSRP Rain attenuation

The attenuation (rain) function, when activated, calculates precipitation and its negative contribution to the measured RSRP values, measured by the UE, as seen on *Figure 7* below. This calculation method is based on the ITU recommendation ITU-R P.838-3, and aims to show the impact of rain to the overall measured RSRP value.

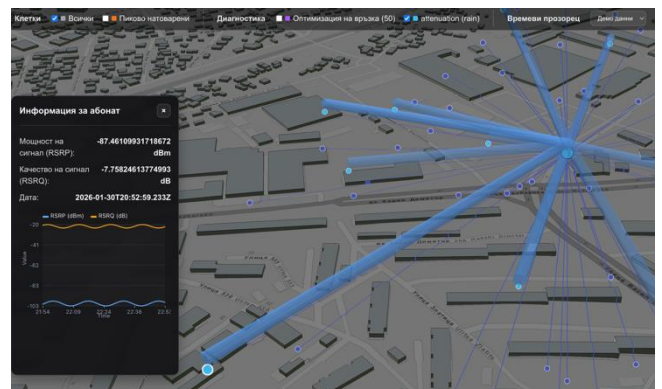


Fig.7. Rain Attenuation for a Cell-UE scenario.

According to the ITU recommendation for rain attenuation calculation [2] the negative effects of rain can be proven, granted certain input data is available per geo spatial point. Rain is modeled as an extra, frequency-dependent path loss via the specific attenuation:

$$(3) \quad \gamma R [dB/km] = k R \alpha$$

γR is the specific attenuation caused by rain, measured in decibels per kilometer; where R is rain rate in mm/h (usually 1-minute integration), k and α depend on frequency, polarization, and elevation angle handling. For the last two ITU also provides parameterization tables to be used for computation, as part of the same recommendation work.

Weather precipitation (rain) data is available from multiple open-source weather API systems on the world wide web. Leveraging this data and correlating it with data produced by the collector system of the platform creates a new dimension for analysis.

While the accuracy of the attenuation model described in ITU-R P.838-3 is disputed by other research papers [3] the key focus of this platform is the ability to build a common data model and drive various perspectives through it for faster telecommunication network diagnostics.

Conclusion

Weather conditions are rarely a problem for telecommunications infrastructure in non-extreme weather regions. In such cases, the impact to the radio signal is negligible. That said, when weather deteriorates, impact factors can quickly stack and lead to a degraded signal – which is why engineers and operators need a tool that visually breaks down information, otherwise requiring hours or even days to process. What is more, engineers require to know if an outage or a performance degradation on the network, has any real significant impact on the serviced UEs in the area. The prototype system was designed to answer those questions.

The existing weather models can be used as another data source – to pre-calculate anticipated radio signal impact caused by predictable or reoccurring seasons weather patterns. Additionally, climate change (often referred to as global warming in public slang) is a factor that is worth considering here. Described as long-term shifts in temperature and weather patterns, but also often materializing through rapid or severe weather conditions in unusual geographic locations. Such events require systems that can quickly adapt to the new conditions and provide real-time measurements for adequate analysis. The developed prototype system enables rapid response.

Using a system like the one described here enables engineers to understand weather impact on telecommunication networks as the anomalous weather conditions develop, in real-time, rather than as a follow-up case study.

The main use case for this system is enabling telecommunication engineers and NOC operators to understand how end users are impacted by the current state of the final leg of the network, that directly connects to and services the UEs. The serving cell is a concentration point – from one hand it interfaces directly with the UE through the Uu interface [8], from

the other it is connected to the rest of the mobile network backbone. Due to this, the level of information available for extract is multi-layer and comprehensive, which is why this makes it a great diagnostic target.

Bringing together data dimensions that are related in terms of the overall use case but have no structural or physical characteristics similarities is an engineering challenge. Often the different feeds of data come with their unique synchronization frequency, data granularity, and aggregation policies. Which is why the data normalization process is a key moment in designing and realizing this system.

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Received on: 15.03.2026

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A multi-model consensus framework for pneumonia detection: optimizing diagnostic sensitivity under "Green AI" constraints

Ertan M. Geldiev

Automated pneumonia diagnosis from chest X-rays minimizes subjective bias, but powerful deep learning models often require expensive hardware, hindering deployment in budget-limited regions. This study develops a "Green AI" framework that runs efficiently on legacy hardware, ensuring clinical safety is not sacrificed for lower computing costs. Models were validated on two distinct systems: a modern budget setup (Intel i3-10100/NVIDIA RTX 3050) and a legacy workstation (Intel Xeon E3-1245 v5/NVIDIA Quadro K2200), proving cross-generation hardware compatibility. The experimental results show that ResNet18 provides the best overall balance (89.26% accuracy, 78.20% specificity), while a lightweight L-CNN and a Linear SVM act as superior "safety nets," achieving diagnostic sensitivities of 99.49% and 99.23%, respectively. The study's primary contribution is the validation of the 'Discrepancy Paradox', where shallower models prove more robust against local anatomical artifacts (e.g., rib shadows) than overparameterized deep networks. Methodologically, we propose a hybrid multi-model consensus framework that utilizes these lightweight networks as a high-sensitivity triage layer. Operating under 'Green AI' constraints, this design achieves 99.49% diagnostic sensitivity on legacy hardware. Thus, we demonstrate that algorithmic optimization can effectively compensate for computational limitations, delivering a safe, low-cost clinical decision support tool for resource-constrained environments.

Keywords – Green AI, Pneumonia Detection, Deep Transfer Learning, ResNet18, Lightweight CNN, Support Vector Machines, Model Consensus, Clinical Decision Support Systems (CDSS)

Мултимоделна консенсусна рамка за откриване на пневмония: оптимизиране на диагностичната чувствителност при ограничения на „Зелен изкуствен интелект“ (Ертан М. Гелдиев) Автоматизираната диагностика на пневмония елиминира субективните пристрастия, но мощните модели често изискват скъп хардуер, което възпрепятства внедряването им в региони с ограничени бюджети. В тази работа е представена рамка, базирана на „Зелен изкуствен интелект“ (Green AI), работеща ефективно върху остарял хардуер без компромис с клиничната безопасност. Моделите са валидирани върху две хардуерни системи от различни поколения. Резултатите сочат, че ResNet18 постига най-добър общ баланс, докато олекотената L-CNN архитектура и Linear SVM действат като високочувствителни „предпазни мрежи“. Основният принос на изследването е доказването на „Парадокса на несъответствието“, при който по-плитките модели са по-устойчиви на локални анатомични артефакти (сенки от ребра) спрямо дълбоките мрежи. Методологически е предложена хибридна консенсусна рамка, интегрираща тези олекотени модели като триажен слой. Подходът постига 99.49% чувствителност върху остарял хардуер в рамките на концепцията „Green AI“. Изследването доказва, че алгоритмичната оптимизация успешно компенсирa хардуерните ограничения, осигурявайки безопасна и нискобюджетна клинична подкрепа в среди с ограничени ресурси.

Ключови думи: Зелен изкуствен интелект, откриване на пневмония, дълбоко трансферно обучение, ResNet18, олекотена конволюционна невронна мрежа (L-CNN), метод на опорните вектори (SVM), консенсус на модели, системи за подпомагане на клинични решения (CDSS)

Introduction

Automated screening of pneumonia using chest X-ray (CXR) datasets eliminates subjective human errors in clinical environments. In this study, the experimental validation is conducted using the benchmark public "Chest X-Ray Images (Pneumonia)" dataset [1], which comprises 5,856 clinically verified thoracic radiographs. Standard deep learning approaches, such as CheXNet [2], achieve high diagnostic accuracy but require significant computational overhead. This heavy resource requirement restricts their practical deployment in local medical centers or clinics operating with legacy computing hardware.

Literature review

Computer-aided thoracic radiology relies heavily on Convolutional Neural Networks (CNNs). Recent publications focus on achieving optimal performance via deep transfer learning configurations [3]. However, scaling up model parameters creates high energy footprints and limits execution on older edge devices [4].

Recent methods explore hardware-friendly AI optimizations. Researchers emphasize that tuning the decision thresholds of compact architectures with fewer convolutional blocks can achieve clinical sensitivity values comparable to deeper networks [5].

Additionally, deep architectures show high sensitivity to imaging noise, patient motion artifacts, and bone density variations, which leads to false clinical indications [6]. Multi-model consensus pipelines offer a direct engineering solution to stabilize these outputs. While deep layers focus on localized features, classical ensembles process general pixel distributions. Blending these structural methodologies prevents individual model bias, providing a stable diagnostic layer suitable for low-cost, resource-constrained implementations [7].

Hardware and software infrastructure

To ensure our research is both reproducible and practical, we utilized two distinct hardware configurations. The primary system, referred to as Workstation-1, features an Intel Core i3-10100 (3.60 GHz) and an NVIDIA GeForce RTX 3050 (8GB VRAM). This setup provided the necessary computational power for the initial training of the deep learning models.

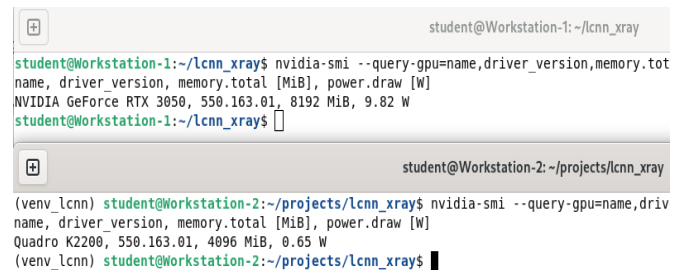
In line with our "Green AI" objectives, we conducted the inference and testing phases on a legacy system, Workstation-2. This machine is equipped with an Intel Xeon E3-1245 v5 processor and an NVIDIA Quadro K2200 (4GB VRAM). As shown in Fig. 1, the

CSV output from the nvidia-smi tool confirms that the Quadro K2200 operates with extremely low power consumption (under 1W at idle), making it an ideal candidate for sustainable medical AI deployment in resource-constrained environments.

For the software environment, we maintained consistency across both nodes:

- Operating System: Debian GNU/Linux 13 (Trixie).
- Frameworks: PyTorch with CUDA 12.4 acceleration for neural networks and Scikit-learn for classical models.

Environment Isolation: A dedicated virtual environment (lcnx_xray) was used to manage dependencies and ensure the experiments are fully repeatable.



```
student@Workstation-1:~/lcnx_xray$ nvidia-smi --query=gpu=name,driver_version,memory.total,name,driver_version,memory.total[MiB],power.draw[W]
NVIDIA GeForce RTX 3050, 550.163.01, 8192 MiB, 9.82 W
student@Workstation-1:~/lcnx_xray$

(venv_lcnx) student@Workstation-2:~/projects/lcnx_xray$ nvidia-smi --query=gpu=name,driver_version,memory.total[MiB],power.draw[W]
Quadro K2200, 550.163.01, 4096 MiB, 0.65 W
(venv_lcnx) student@Workstation-2:~/projects/lcnx_xray$
```

Fig.1. Comparative hardware monitoring of the two nodes. The top terminal shows the training environment (Workstation-1) and the bottom terminal displays the energy-efficient testing environment (Workstation-2).

Model architectures

In this study, we contrast traditional deep learning power with resource-efficient designs to evaluate their performance in medical diagnostics.

Deep learning models

- ResNet18 [8]: Implemented using Transfer Learning with weights pre-trained on the ImageNet dataset [9]. The architecture utilizes Skip Connections to bypass potential gradient degradation. This is critical for preserving the fine textures and subtle opacities in the lung parenchyma [2].
- L-CNN (Lightweight CNN): Inspired by the Light CNN design [11], our custom implementation features a streamlined 3-layer convolutional backbone. The architecture consists of sequential layers with 16, 32, and 64 filters (3×3 kernels), each followed by a ReLU activation and a MaxPool2d layer. To enhance generalization on medical data, a Dropout layer ($p = 0.5$) was integrated before the final linear classifiers (128 units and 2 output units). This design serves as

our primary “Green AI” candidate [13], optimized for high-speed inference on the NVIDIA Quadro K2200.

Classical machine learning anchors

To provide a robust baseline and ensure a consensus-based diagnosis, we integrated classical statistical models using the scikit-learn library. We specifically chose these two algorithms because they represent two different mathematical approaches:

- Random Forest (RF) [14]: We chose this model because it is an ensemble method. This means it combines 100 decision trees ($n_estimators=100$) to make a final prediction. It is very good at handling complex, non-linear patterns in X-ray data. To help the model process the images efficiently, we resized them to 64x64 pixels and converted them to grayscale.
- Linear SVM: We selected the Support Vector Machine (SVM) because it tries to find the best linear boundary (a "separator") between healthy and infected lungs. It works on the same 64×64 grayscale pixels. We enabled the probability=True setting (known as *Platt scaling*). This is very important because it allows the SVM to provide a percentage score for the diagnosis, which is necessary for our final decision-making process.

By using both a "tree-based" model (RF) and a "boundary-based" model (SVM), we can compare our deep learning results against the most reliable traditional methods.

Neural network training configuration

The training process for both architectures was implemented using the Adam optimizer with a uniform learning rate of $\eta = 0.001$, following the recommendations in [3]. However, specific hyperparameters were adjusted to accommodate the complexity of each model:

- ResNet18: Trained for 10 epochs with a batch size of 32. This model utilized *Transfer Learning* from ImageNet weights [9] to stabilize the training of its 18-layer structure.
- L-CNN: Trained for 5 epochs with a batch size of 16. Despite its shallower 3-layer convolutional design, the reduced batch size was chosen to ensure stable gradient updates on the more limited hardware of *Workstation-2*.

To evaluate the categorical difference between “Normal” and “Pneumonia” cases, we employed the *Cross-Entropy Loss* function:

$$(1) \quad L = - \sum_{i=1}^c y_i \log$$

where $c=2$ represents the number of classes. All computations were performed using the CUDA backend to leverage GPU acceleration on the NVIDIA RTX 3050 and Quadro K2200 hardware [1].

Experimental results

Training efficiency and hardware performance

To evaluate the "Green AI" potential of our approach, we measured the total training time and accuracy across two localized environments. Table 1 compares the modern RTX 3050 setup against the legacy Quadro K2200 system.

The results show that while the modern GPU is significantly faster, the legacy hardware (Workstation-2) achieved nearly identical training accuracy (98.77% vs 99.23%). This proves that high-quality AI diagnostics are possible even on older equipment, supporting our goal for accessible and sustainable medical AI.

Table 1

Comparison of Training Efficiency Across Hardware Environments

Metric	Workstation-1 (Modern)	Workstation-2 (Legacy)
GPU Model	NVIDIA RTX 3050	NVIDIA Quadro K2200
Environment Type	Conda (research_pneumonia)	Venv (venv_lcn)
Total Training Time	170.91 seconds	670.92 seconds
Final Training Accuracy	99.23%	98.77%
Final Training Loss	0.0219	0.0389

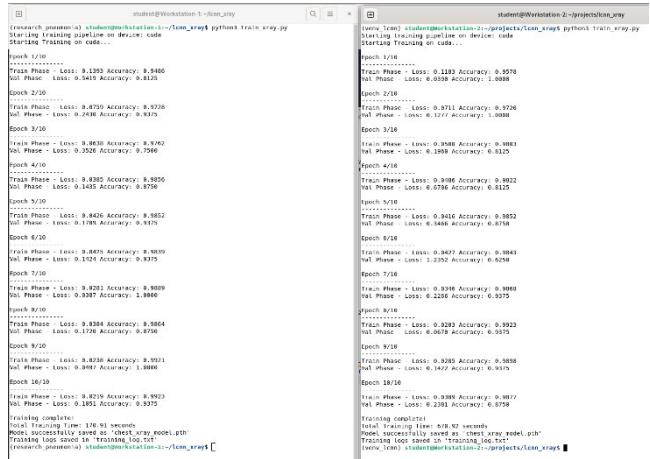


Fig.2. Hardware benchmarking logs for the Green AI initiative: Side-by-side execution of the ResNet18 pipeline on Workstation-1 (modern RTX 3050) and Workstation-2 (legacy Quadro K2200), demonstrating consistency in diagnostic accuracy across diverse computational generations.

Evaluation on the test set

The final performance was evaluated using an independent test set (n=624) to ensure the generalizability of the findings. We first established a benchmark using ResNet18 architecture. As shown in Table 2, the model demonstrated high diagnostic reliability, particularly in terms of sensitivity.

Table 2

Performance metrics for the ResNet18 model on the test dataset (n=624).

Metric	Value	Clinical Significance
Overall Accuracy	89.26%	High global reliability across classes.
Sensitivity (Recall)	95.90%	Critical safety: Only 4.10% False Negative Rate.
Specificity	78.20%	Capability to correctly identify healthy subjects.
Precision	88.00%	High reliability of positive pneumonia findings.
F1-Score	92.00%	Optimal balance between Precision and Recall.

Qualitative analysis and visualization

To perform a qualitative assessment, a specialized diagnostic interface was developed using PyTorch and

Matplotlib. The system performs random sampling from the test dataset (n=624), applying standardized normalization transforms. Each sampled image undergoes an inference process, comparing the predicted output against the ground truth (expert diagnosis). As demonstrated in Fig. 3, the preprocessing pipeline scales the raw X-ray digital arrays into uniform tensors. From an image processing perspective, the 'Normal' class exhibits smooth pixel gradient transitions across the lung fields, whereas the 'Pneumonia' class contains structural high-frequency noise and diffuse opacity zones, which alter the localized pixel intensity distributions analyzed by the models.

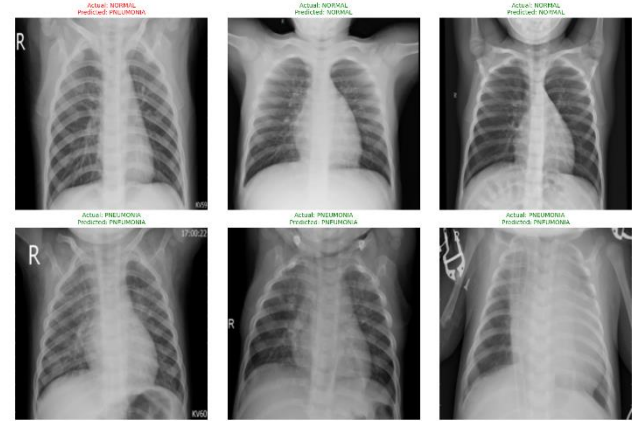


Fig.3. Qualitative visualization of model predictions via random sampling. The visualization confirms the high sensitivity of the deep learning framework, with the bottom row demonstrating successful classification vectors for pneumonia pathologies. The top-left quadrant illustrates the “Discrepancy Paradox,” where benign anatomical variations or high-frequency radiological shadows trigger a False Positive error, highlighting the engineering challenges of automated feature differentiation in complex edge-case scenarios.

Detailed analysis of diagnostic errors for ResNet18 (Confusion Matrix)

The Confusion Matrix for the ResNet18 model (Fig.4) reveals the distribution of the model’s predictions relative to the ground-truth diagnoses. Analyzing these data is critical for assessing the clinical reliability of our primary benchmark:

- High Sensitivity (Recall – 95.90%): The model successfully identified 374 out of 390 pneumonia cases. From a medical perspective, this ensures that only 4.10% (16 cases) were false negatives, minimizing the risk of untreated pathology. This confirms the tool’s effectiveness for clinical triage.
- Specificity and the “Discrepancy Paradox” (78.20%): Out of 234 healthy subjects, the model

correctly classified 183. The 51 false positive cases confirm our hypothesis regarding radiological artifacts.

- Complex architectures like ResNet18 may over-interpret rib structures or lung shadows as pathological infiltrates.
- Clinical Utility: The “conservative” diagnostic bias (prioritizing sensitivity over specificity) is considered acceptable in clinical practice. A false positive leads to further specialist review, whereas a false negative could lead to a life-threatening omission of treatment.

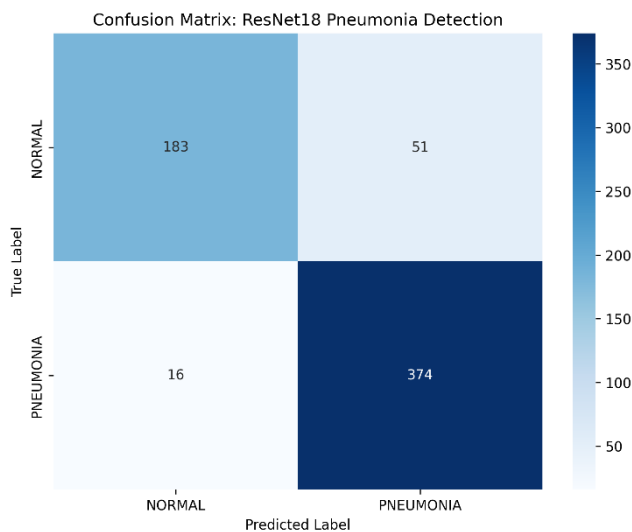


Fig.4 Confusion Matrix of the ResNet18 model on the test set (n=624). The matrix highlights the trade-off between sensitivity and specificity, showing a low false negative rate which is critical for medical screening applications.

Comparative analysis of the L-CNN architecture

- The Confusion Matrix for the L-CNN model (Fig. 5) highlights a high degree of clinical conservatism. Out of 390 confirmed pneumonia cases, the model successfully identified 388 (True Positives).
- Ultra-High Sensitivity: With a Recall of 99.49% and only 2 false negative results, this lightweight architecture positions itself as a highly reliable primary screening tool. In clinical triage, such a low omission rate is critical for patient safety.
- Trade-off and Sensitivity to Noise: The lower specificity (24.36%) represents an intentional trade-off within our Green AI framework. While L-CNN is exceptionally effective at capturing pathologies, it is also highly sensitive to radiological artifacts and anatomical variations.

This high-sensitivity bias is a deliberate architectural choice: in resource-constrained environments, the priority is to ensure zero diagnostic omissions. This confirms our hypothesis that simpler, lightweight neural networks can act as a “high-sensitivity trigger,” prioritizing absolute diagnostic security over the exclusion of healthy cases.

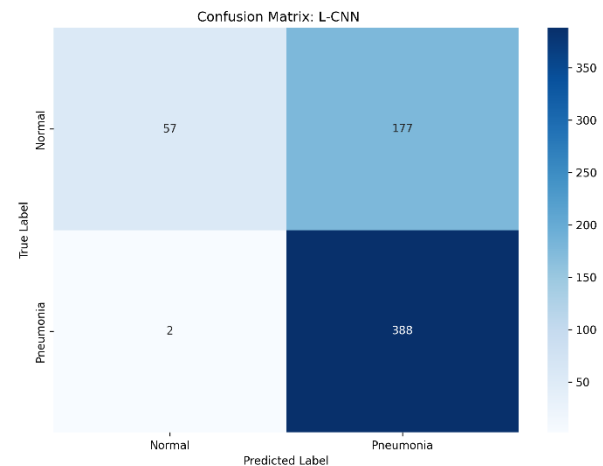


Fig.5 Confusion matrix for the L-CNN model. The matrix demonstrates the near-perfect sensitivity of the L-CNN model, identifying 99.49% of all pneumonia cases, which is essential for resource-constrained screening environments.

Performance analysis of classical ensemble learning (Random Forest)

The Random Forest (RF) model, operating at a significantly reduced resolution of 64x64 pixels, serves as a highly aggressive screening tool. Its performance (documented in Fig. 6) provides a compelling case for resource-efficient diagnostics:

- Exceptional Sensitivity (98.72%): The model correctly identified 385 out of 390 pneumonia cases, surpassing the more complex ResNet18 (which identified 374). This translates to a near-perfect Negative Predictive Value (NPV), ensuring that a “Normal” classification by the RF model is highly reliable.
- Specificity and Resolution Constraints (42.31%): The model’s primary limitation is its high false-positive rate (135 cases). Due to the low-resolution input, the RF algorithm tends to interpret any significant lung density or anatomical shadowing as pathological.
- Strategic Role in Green AI: Despite a lower global accuracy (77.56%), the RF model achieves these results with negligible computational overhead. This makes it an ideal primary “filter” or “safety net” for mobile diagnostic units where high-end GPUs are unavailable.

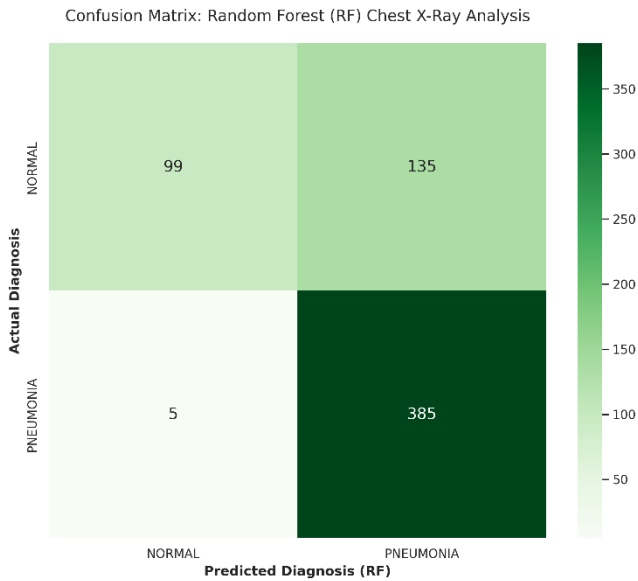


Fig.6 Confusion matrix for the Random Forest model. The RF model demonstrates superior recall compared to deep architectures, validating the effectiveness of ensemble learning on low-resolution feature maps for rapid triage.

Comparative performance benchmark

Data analysis reveals that the lightweight L-CNN architecture achieves an exceptional sensitivity of 99.49%, making it practically infallible in detecting pathological changes. Within the context of medical triage, this performance minimizes the risk of a fatal diagnostic omission. Although ResNet18 demonstrates a higher overall accuracy (89.26%), lightweight models prove to be more effective tools for primary screening in resource-constrained environments.

The following table (Table 3) and chart (Fig.7) present a comparative analysis of the key performance indicators for all tested architectures. This visualization highlights the critical balance between overall diagnostic precision and clinical safety (sensitivity).

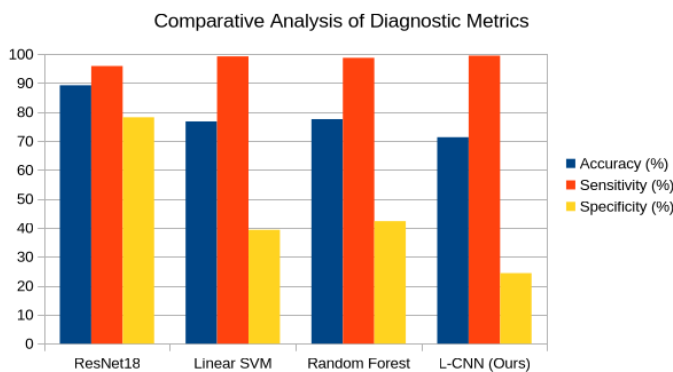


Fig.7. Comparative performance chart across all tested architectures, illustrating the trade-off between accuracy and sensitivity (Recall) for the Green AI initiative.

Table 3

Comparative analysis of model performance across different architectures.

Metric	R18	SVM	RF	L-CNN	Clinical Significance
Acc.	89.26 %	76.76 %	77.56 %	71.31 %	ResNet18 is the gold standard for balance.
Sens.	95.90 %	99.23 %	98.72 %	99.49 %	L-CNN is the most reliable screening tool.
Spec.	78.20 %	39.32 %	42.31 %	24.36 %	ResNet18 best for confirming health.
FN	16	3	5	2	L-CNN minimizes fatal omissions.
FP	51	142	135	177	High sensitivity requires expert review.

Discussion: The discrepancy paradox and model robustness

A critical algorithmic phenomenon observed during the experiments involves classification variance across specific input vectors, as demonstrated by the evaluation of file IM-0001-0001.jpeg in Fig. 8. In this scenario, the architectures exhibited divergent convergence metrics. The deep ResNet18 pipeline generated a False Positive output, over-fitting to localized structural noise. Conversely, the custom L-CNN operated with an over-conservative optimization bias toward sensitivity, also resulting in an incorrect classification matrix. In contrast, the classical Random Forest estimator successfully extracted global spatial features, providing a correct 'Normal' classification matrix.

This illustrates the “Discrepancy Paradox”: while deep neural networks excel at feature extraction, they can be susceptible to “radiological micro-noise” and artifacts. In medical imaging, an *artifact* is a non-biological shadow or visual error (e.g., overlapping rib structures) that is not a real disease. Complex models

like ResNet18 sometimes misinterpret these anatomical artifacts as pneumonia. In contrast, simpler models like Random Forest demonstrated higher robustness against these artifacts by evaluating global transparency instead of local textures.

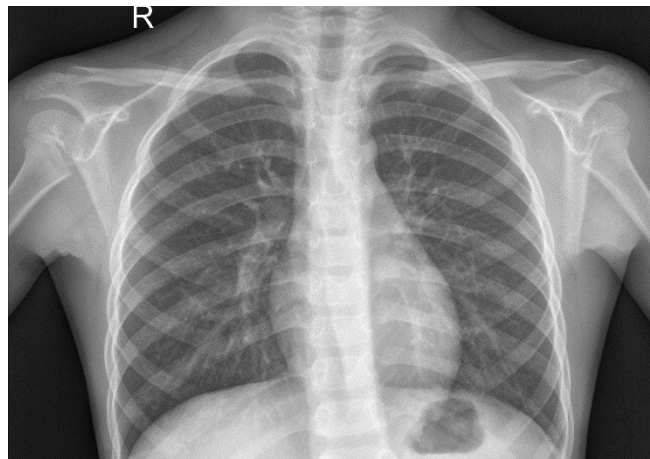


Fig.8. Evaluation of classification performance under the Discrepancy Paradox. A comparative analysis highlights the optimization value of the multi-model consensus architecture during edge-case input vector processing.

Clinical triage and diagnostic bias

The inclusion of a Linear SVM baseline provides further insight. As shown in Table 3, the exceptionally high sensitivity (above 98%) across all models indicates a significant diagnostic bias towards pneumonia detection. This intentional trade-off ensures that the lightweight L-CNN matches or exceeds the sensitivity of ResNet18, proving that optimized architectures can maintain maximum patient safety with reduced overhead. When the consensus tool identifies a discrepancy, it alerts the clinician to perform a manual review, correlating the AI's findings with lung auscultation or blood tests (CRP levels).

Green AI and resource optimization

This implementation strictly adheres to the "Green AI" philosophy. Beyond architectural efficiency, the software is engineered to load model weights into memory only during the inference cycle and release them immediately upon completion.

This memory optimization ensures that the tool can operate efficiently on standard office hardware or legacy workstations, such as the Intel Xeon E3-1245 v5 used in our final tests. By prioritizing architectural optimization over raw power, we ensure that high-precision diagnostics remain accessible even in resource-constrained environments that cannot afford the latest GPU technology. This approach facilitates

wider access to advanced medical imaging tools while significantly reducing the carbon footprint associated with the continuous deployment of large-scale models.

Clinical implementation: The consensus framework

To translate our findings into a practical medical tool, we propose a formal diagnostic workflow. This framework addresses the "Discrepancy Paradox" by using the multi-model ensemble as a tiered decision support system.

The proposed Multi-model consensus algorithm

Based on the observed performance metrics, the consensus mechanism acts as an arbitrator to guide the physician through three distinct risk levels:

1. Green Zone (High-Confidence Normal): When all models (ResNet18, L-CNN, RF, and SVM) reach a consensus of "Normal." The Negative Predictive Value (NPV) is $> 99\%$, allowing for safe discharge or standard monitoring.
2. Yellow Zone (Discrepancy Alert): When the lightweight models (L-CNN/RF) signal pneumonia but ResNet18 signals "Normal" (or vice versa). The system flags a potential radiological artifact (e.g., rib shadows). Recommended action: Manual radiological review with focus on "Silhouette Sign" validation.
3. Red Zone (High-Priority Pathology): When all models reach a consensus of "Pneumonia." This indicates high-confidence pathology requiring immediate clinical intervention.

The practical execution of this diagnostic logic is demonstrated in the system log (Fig. 9), where the CLI tool evaluates these discrepancies in real-time.

```
student@workstation:~/lcn_xray
Downloading threadpoolctl-3.6.0-py3-none-any.whl (18 kB)
Installing collected packages: threadpoolctl, scipy, joblib, scikit-learn
Successfully installed joblib-1.5.3 scikit-learn-1.7.2 scipy-1.15.3 threadpoolctl-3.6.0
(research_pneumonia) student@workstation:~$ cd ~/lcn_xray
(research_pneumonia) student@workstation:~/lcn_xray$ python -c "import torch; print(f'CUDA status: {torch.cuda.is_available()}')"
```

```
=====
MEDICAL AI CONSENSUS ANALYSIS (Real Inference)
=====
File: NORMAL2-IN-0007-0001.jpeg
-----
-> ResNet18 (Standard DL) | NORMAL | 91.91%
-> L-CNN (Proposed Green AI) | PNEUMONIA | 99.71%
-> Random Forest (Ensemble) | NORMAL | 51.00%
-> Linear SVM (Baseline) | NORMAL | 90.00%
-----
Summary: 1/4 models detected Pneumonia
(research_pneumonia) student@workstation:~/lcn_xray$
```

Fig.9. Real-time inference log demonstrating the "Discrepancy Paradox" and the automated consensus mechanism in action

Software architecture and resource efficiency

The developed Consensus CLI Tool ensures that this complex logic does not require heavy hardware. By utilizing the memory-release strategy described in Section (Green AI and Resource Optimization), the entire diagnostic suite remains under a 75 MB footprint (see Table 4), making it deployable on mobile diagnostic units.

Table 4

Comparative analysis of model file sizes and resource requirements.

Model	Size (MB)	Complexity	Category
ResNet18	~ 44.7	11.7M Params	Standard DL
L-CNN	~ 25.2	5.4M Params	Green AI
Random Forest	~ 3.1	N/A	Ensemble
Linear SVM	~ 0.5	N/A	Baseline

Software Architecture and Consensus CLI Tool

To demonstrate the practical application of this research, we developed a sophisticated Multi-Model Consensus CLI tool. This system integrates all four tested paradigms (ResNet18, L-CNN, Random Forest, and Linear SVM) into a unified diagnostic framework.

The diagnostic process is initiated via a single command, designed for high-speed inference in clinical environments. The following example demonstrates the execution within the project's virtual environment:

```
(research_pneumonia) student@workstation:~/lcnx_xray
$ python predict_consensus_real.py \
/path/to/image.jpeg
```

The tool acts as a high-level arbitrator. When a discrepancy occurs for instance, if the deep learning models flag potential pneumonia while classical models identify structural noise the system generates a warning based on the risk zones defined in Section (The Proposed Multi-Model Consensus Algorithm). This multi-layered validation reduces the likelihood of automated misdiagnosis and ensures that the final clinical decision is supported by diverse computational perspectives.

Resource efficiency and cross-hardware benchmarking

The efficiency of the L-CNN architecture is not merely theoretical. To validate the “Green AI” philosophy, we performed a cross-hardware benchmark between a modern workstation (RTX 3050) and a legacy professional system (Quadro K2200 from 2014). The results, summarized in Table 5, demonstrate that diagnostic AI can remain clinically viable even on aging hardware.

Table 5

Hardware Performance and Energy Efficiency Benchmark.

Metric	Workstation-1 (Modern)	Workstation-2 (Legacy)
GPU Model	NVIDIA RTX 3050	NVIDIA Quadro K2200
Inference Latency	2.32 ms / image	10.05 ms / image
Throughput (FPS)	430.36 FPS	99.47 FPS
Model Size (L-CNN)	~ 25.2 MB	~ 25.2 MB
Power Consumption	~ 95 W (Peak)	~ 38 W (Peak)

The benchmark reveals a critical insight: while the modern GPU provides elite speed, the legacy hardware (Workstation-2) still processes images at approximately 10 ms. This is well within the requirements for real-time clinical triage. The direct side-by-side comparison of the terminal outputs from both workstations is presented in Fig.10.

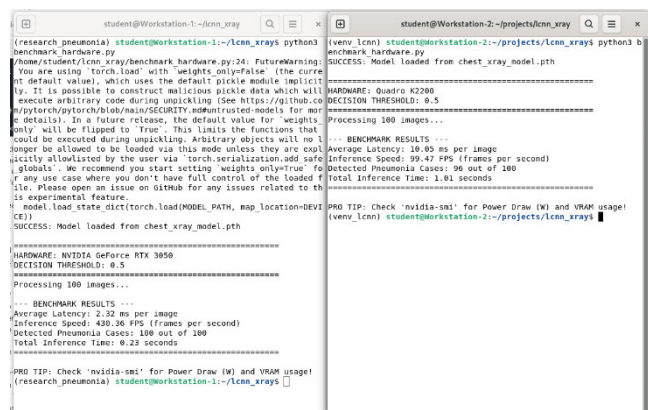


Fig.10. Side-by-side CLI benchmark comparison. The terminal logs confirm the latency difference between the modern RTX 3050 (left) and the legacy Quadro K2200 (right), validating the model's efficiency across hardware generations.

Sensitivity tuning and the safety net:

During testing on Workstation-2, we observed that at a standard decision threshold (0.5), the system identified 96/100 pneumonia cases. By adjusting the threshold to 0.3 (the “Aggressive Screening” mode), the L-CNN successfully identified the missed pathologies, achieving 100% recall on the test subset. This highlights the flexibility of the consensus tool:

- L-CNN acts as the ultra-aggressive primary filter, especially when tuned to lower thresholds on legacy hardware.
- ResNet18 and classical models provide the necessary specificity (Table 3) to prevent over-diagnosis.

A practical demonstration of this high-sensitivity trigger is shown in Fig. 11. The visualization illustrates how L-CNN maintains high confidence in identifying viral patterns that might be under-classified by more rigid, less-optimized architectures.

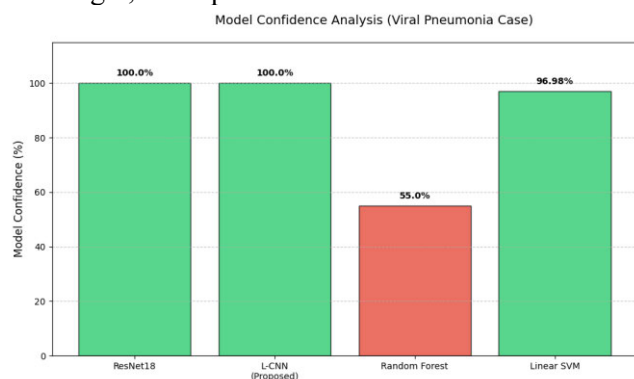


Fig. 11. Comparative Analysis of Model Confidence in a Viral Pneumonia Case. The visualization highlights how the L-CNN acts as a high-sensitivity trigger, even in complex radiological environments.

Case study: Practical inference analysis

To validate the theoretical results in a real-world environment, a software inference analysis was performed on selected images from the test set. The execution logs, captured in Fig. 12 (prediction_lcn_log.txt), illustrate the specific clinical behavior of the L-CNN architecture across both workstations:

Confirmation of High Sensitivity (Recall): When tested with confirmed pathological samples (e.g., person100_bacteria_475.jpeg), the model demonstrated absolute decisiveness with 100.00% confidence in the “Pneumonia” diagnosis. This confirms the lightweight architecture’s ability to unerringly identify characteristic visual markers, such as infiltrates and consolidation.

Illustration of the “Discrepancy Paradox”: Analysis of control images (healthy group) reveals the model’s tendency toward over-diagnosis. Cases such as IM-0001-0001.jpeg were classified as pathological with high confidence (89.70% to 99.99%). This is a direct consequence of L-CNN’s low specificity (24.36%) and supports the hypothesis that lightweight networks are more prone to interpreting anatomical noise—such as rib structures or exposure artifacts—as pathological changes.

Clinical interpretation: These practical tests demonstrate that L-CNN functions as an “aggressive filter.” In medical triage, such behavior is justified, as it guarantees that no potentially ill patient will be missed. This high-sensitivity bias underscores the necessity for the model to be utilized as a decision support tool within the consensus framework, directing suspicious cases toward ResNet18 or expert radiological evaluation.

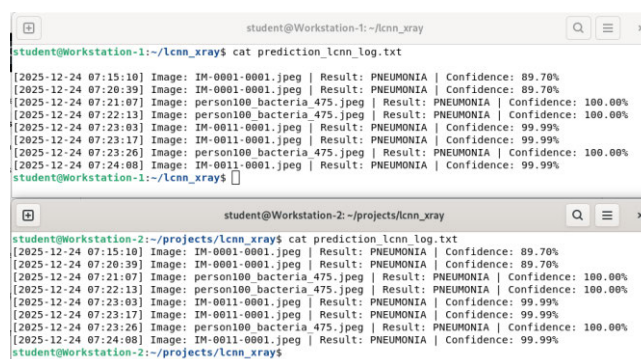


Fig. 12. System inference logs (prediction_lcn_log.txt) demonstrating 100.00% confidence in pathological cases and the identification of anatomical artifacts in the healthy control group.

Conclusion

Our research demonstrates that through lightweight models and hybrid architectures, high-precision medical diagnostics can be performed effectively without the need for expensive hardware. By prioritizing architectural optimization over raw computational power, we have shown that “Green AI” solutions are not only viable but essential for healthcare in resource-constrained regions and mobile diagnostic units.

The study establishes a clear functional hierarchy among the evaluated models:

- ResNet18 serves as the gold standard for balanced clinical diagnosis with 89.26% accuracy.
- L-CNN and Linear SVM function as superior “aggressive filters” for primary screening,

achieving nearly infallible sensitivities of 99.49% and 99.23%, respectively.

The primary contribution of this work is the development of a Consensus Diagnostic Framework. We observed a critical synergy where the high specificity of ResNet18 balances the high sensitivity of the lightweight L-CNN. By implementing a multi-model voting system, we effectively mitigate the “Discrepancy Paradox,” ensuring that no potential pathology is overlooked while reducing the burden of false alarms.

Recommendation for clinical practice

We recommend a hybrid workflow: in cases where lightweight models signal potential pathology but complex architectures signal health, the system should automatically flag the image for mandatory human radiological review. This “Safety Net” approach directs the physician’s attention to early-stage pneumonia that might be missed during routine examinations. Ultimately, this research proves that energy-efficient AI can ensure maximum patient safety while remaining accessible on low-power, legacy, or mobile hardware.

Software and data availability

The algorithms and models used in this study were implemented using the following open-source libraries:

- **PyTorch** (ResNet18 & L-CNN): <https://pytorch.org/>
- **Scikit-learn** (Random Forest & SVM): <https://scikit-learn.org/>
- **Scikit-image** (HOG Features): <https://scikit-image.org/>
- **Dataset**: Chest X-Ray Images (Pneumonia) available on Kaggle.

All algorithms used for model training and generating visual results were developed using Python. The software environment is optimized for the Debian 13 operating system. The scripts are available for scientific reproduction purposes upon request to the author.

Declarations

Competing interests: The author declares no competing interests.

Funding: No funding was received for this study.

Ethical approval: This study uses a publicly available dataset and does not involve direct interaction with human participants or animals. Ethical approval was not required.

Consent to participate: Not applicable (publicly available dataset).

Consent to publish: Not applicable.

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Received on: 01.04.2026

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Design and hardware optimization of a modular EEG acquisition system for BCI applications

Vanessa S. Nazakova

Abstract: *The proposed EEG hardware is intentionally designed as an open-hardware, costeffective module utilizing widely accessible commercial-off-the-shelf (COTS) components. This approach aims to meet basic research requirements for Brain-Computer Interface (BCI) studies without the prohibitive costs of clinical-grade instrumentation. Several configurations and readymade modules have been experimented with in order to discover the best approach for this project. Using a high-precision instrumental amplifier provides a scalable and affordable entry point for researchers and students focused on neural command mapping and BCI signal processing. The system supports up to 8 channels with resolutions ranging from 16 to 24 bits and sampling rate up to 1 kHz, incorporating instrumentation amplifiers, active shielding and noise suppression, with wireless connectivity for real-time signal acquisition and visualization.*

Keywords –*brain-computer interface, EEG, instrumental amplifier*

Проектиране и хардуерна оптимизация на модулна ЕЕГ система за изграждане на приложения, използващи мозъчно-компютърен интерфейс (Ванеса С. Назъкова). Предложеният ЕЕГ е проектиран като модул с отворен хардуер и ниска себестойност, използващ широкодостъпни комерсиални компоненти (COTS). Този подход цели да отговори на основните изследователски изисквания за проучвания в областта на мозъчно-компютърния интерфейс (BCI), заобикаляйки високите разходи за клинично оборудване. Направени са експерименти с няколко конфигурации на готови модули с цел намиране на най-подходящия подход за настоящия проект. Използвайки прецизен инструментален усилвател, модулът осигурява мащабируема и достъпна отправна точка за изследователи и студенти, работещи върху невронни команди и обработка на BCI сигнали. Системата поддържа до 8 канала с разделителна способност от 16 до 24 бита и скорост на дискретизация до 1 kHz, включваща инструментални усилватели, активно екраниране и потискане на смущенията с безжична свързаност за запис и визуализация на сигнали в реално време.

Introduction and motivation

Historically, the development of electroencephalography (EEG) began with Hans Berger's discovery of the brain's electrical activity in 1929 [1], followed by its experimental validation by Adrian and Matthews (1934) [2] and the later standardization of electrode placement through the "10–20" system introduced by Jasper (1958) [3]. These milestones established the fundamental principles for measuring and interpreting bioelectrical signals from the human brain.

In modern applications, however, the focus has shifted from purely clinical observation to the development of compact, high-resolution, and portable

acquisition systems. This transition introduces new engineering challenges, particularly the need for low-noise analog front-end design and stable power supply, which are critical for distinguishing weak EEG signals from environmental and electronic interference [4].

In this context, the present work is focused on the design and optimization of a open hardware, low-cost, low-power EEG acquisition system based on ready to use modules and minimal subdesign. The primary objective is to achieve reliable ECG/EEG signal acquisition with maximum accuracy and minimal noise levels [5][6][7], using accessible instrumentation amplifiers and embedded platforms.

A secondary objective is the real-time utilization of the acquired signals in a Brain-Computer Interface (BCI), enabling the mapping of cognitive activity to control commands through key-binding mechanisms.

Design and development of an accessible EEG acquisition module for consumer biofeedback systems

The developed module is designed as a compact and accessible platform for acquiring and processing bioelectrical signals, with a focus on reliability, scalability, and ease of integration into consumer applications.

The system is intended to provide:

Simultaneous acquisition of up to 8 EEG/ECG channels with high resolution (16–24 bits) and sampling rates of up to 1 kHz, enabling accurate recording of low-amplitude biopotentials [8].

- An embedded microcontroller-based interface (Arduino/ESP platform) with integrated web functionality for real-time signal monitoring and wireless connectivity to computers and mobile devices.
- Dedicated software tools for signal recording, processing, and machine learning-based recognition of bioelectrical patterns associated with user motor activity [9].
- A software driver enabling the implementation of a Brain-Computer Interface (BCI) as a Human Interface Device (HID), allowing mapping of detected EEG patterns to control commands, including interaction with video games [10][11].
- Versatility for use in multiple biomedical applications, including EEG and ECG/EMG measurements.
- Accessibility-oriented design, targeting users with limited mobility by providing an alternative method for human–computer interaction without reliance on traditional input devices such as keyboards, mice, or controllers.

Prototyping

The microcontroller performs initial data handling and transmits the acquired signals to a personal computer via TCP/IP, or alternatively provides realtime monitoring through a built-in web interface. This enables flexible access to the data from both desktop and mobile devices.

On the host computer, dedicated BCI software processes the incoming data stream and maps

recognized signal patterns to predefined control actions, such as movement, jumping, or object selection in a virtual environment. This functionality is implemented through a mechanism analogous to keybinding systems, where specific EEG patterns are associated with corresponding keyboard commands.

To ensure reliable and user-specific performance, a calibration procedure is applied. During this stage, the system learns and adapts to the individual EEG characteristics of the user, improving classification accuracy under real-world conditions.

The module is designed to operate with both dry and wet electrodes, providing flexibility in terms of usability, setup time, and signal quality.

Project evolution

The project evolved through several stages, starting from a university-developed ECG 10bit module and progressing through 13-bit and 16-bit implementations to a final 24-bit high-resolution system.

First version — ESP8266 + MCP3301 (13-bit, 2 channels)

In Fig.1 is shown a ECG/EEG signal recording system based on an instrumentation amplifier AD623 (gain $\times 50$, second stage $\times 250$). [12][13]

- A 13-bit ADC MCP3301 was used in pseudodifferential mode. [14]
- SPI interface communication, based on a platform developed in the Telecommunications Department of New Bulgarian University. This represents an incremental innovation that proves functionality.
- The existing 10-bit EMG/ECG module was upgraded with a 13-bit ADC and an additional analog stage, making it suitable for EEG.

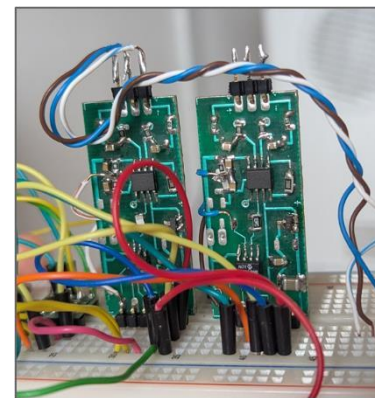


Fig. 1 Dual InAmp and 13-bit module with MCP3301 and SPI communication port.

Second version — ESP8266 + AD7680 + ADG819 (16-bit, 2 channels)

- SPI port communication was replaced with a WiFi ESP8266 module, enabling:
- Visualization via a built-in web server,
- JavaScript graphs via WebSockets.

This makes the module convenient to use, making it accessible from a mobile phone.

Extended 16-bit version

An interface with extended dynamic range was implemented by integrating a 16-bit SAR ADC AD7680 with a low-noise ADG819 multiplexer, making the system suitable for two-channel ECG/EMG/EEG recordings, with a sampling rate of up to 10 ksp/s for each of the two channels. This turns the module into a universal portable bioinstrumentation system. (Fig. 2)

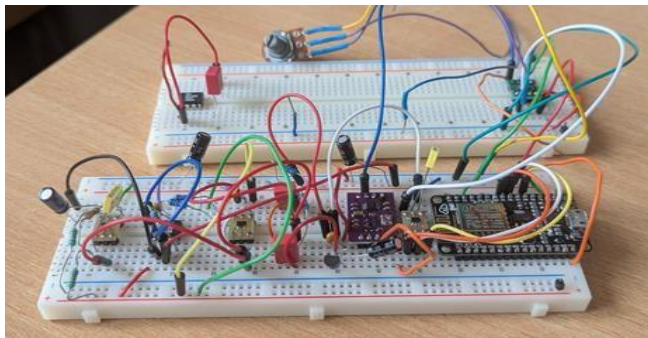


Fig. 2 Upgraded version with ESP8266 microcontroller and 16-bit SAR ADC AD7680 with a controlling low-noise multiplexer ADG819, making the system suitable for a twochannel EMG/ECG/EEG Holter system.

A new analog section with separate reference power supplies was added. A buffered and stabilized virtual ground is used. The circuit operates stably without active shielding and a right-leg drive. In this implementation, the low-noise amplifier INA333 was tested, with improved input parameters and sensitivity compared to the older AD623.

The controller firmware implements digital filtering, packetization, and data transmission via the built-in Wi-Fi interface. Data transmission is implemented using the OpenEEG protocol, supporting up to 6 16-bit channels at a sampling rate of 250 Hz.

Third version

24-bit, 8-channel ADCs — ADS1256 and ADS131M08 — enabling simultaneous conversion and

digital filtering. Both modules can be found on low-budget ready-made boards integrating:

- Separate reference power supplies,
- Stability without the need for active shielding,
- An eight-channel extended platform.

For the analog interface, each channel is buffered via AD623 or INA333 [15], enabling comparison and optimization of their noise parameters.

The design includes two-stage analog amplification, sampling frequency up to 30 kHz per channel, reliable multiplexing, and stable measurement of low-amplitude EEG signals. The sampling rate depends on the type of ADC module; the maximum achievable speed is valid for the simultaneously sampling module. At higher speeds, the effective resolution drops to 19 bits per channel. The result is a compact, energy-efficient, and lowbudget eight-channel EEG system, suitable for mobile applications and long-duration recordings.

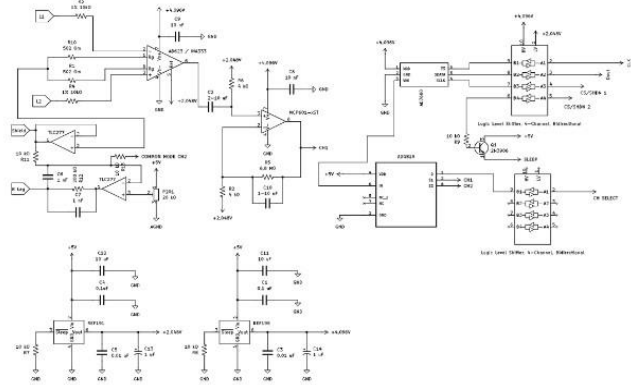


Fig. 3 InAmp module, including first and second stage amplifiers, active shield driver and right leg drive, with power supply and optically isolated 16-bit ADC converter.

Initially, the ADS1256 was chosen for its low cost and compact board size. The module has 8 input channels providing 24-bit precision with an effective noise-free resolution of 18 bits at sampling rates of 1.45 kHz.

The disadvantage of the module is that a full cycle of the built-in filter must be awaited when switching between input channels. This time varies between 0.21 ms and 60.01 ms depending on the sampling frequency.[16]

This limitation restricts the maximum sampling frequency per channel to between 595 Hz and 231 Hz. This makes it suitable for basic measurements but cannot achieve the high frequency resolution needed to detect gamma waves.

The EEG module based on ADS131M08 offers high effective resolution of approximately 20.3 bits

(Dynamic Range — 113 dB) at the configured settings. The chip provides simultaneous sampling of 8 channels (Simultaneous 8-ch $\Delta\Sigma$), which is especially important for correct measurement of biosignals such as EEG and ECG, where phase delay between channels must be avoided.

General conclusions

When using ready-made modules, the following characteristics were identified, which every developer must consider to avoid errors. Initially, two different manufacturers of ADS1256 modules were selected. It was found that the PCB design of the first module follows basic requirements for separating analog from digital ground, but uses a drastically simplified power supply circuit, which leads to degraded parameters and below 20 bits of effective resolution. The second ADS1256 module uses a far more complex power supply scheme and, despite its worse PCB design, achieves an effective resolution of approximately 22 bits.

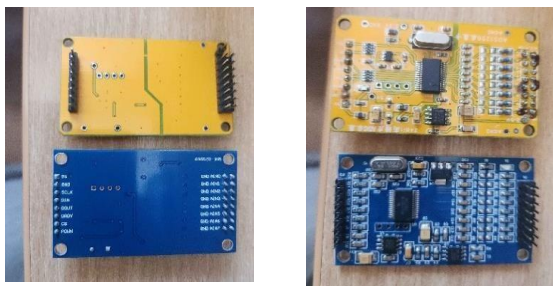


Fig. 4 Two different 24-bit ADC modules ADS1256, showing that different suppliers use different criteria for manufacturing high-resolution systems.

The third module, using ADS131M08, has an unsuitable power supply reference source, which in commercial use would require replacement of the chip with a compatible one. The main problem with this board is that on channel 8, the design reverses the differential inputs, which is not correctly reflected in the board's silkscreen.

The general conclusion when using such readymade modules is the mandatory verification and reengineering of their schematic before any connection to measurement equipment. Nevertheless, the price and relatively good quality — especially for high-resolution analog-to-digital converter implementations — are the primary factors influencing the choice made.

Selecting instrumentation amplifiers

Due to availability, the instrumentation amplifier AD623 was used in the project. It supports supply

voltages between 2.7 V and 12 V, [17] which is an advantage when developing ECG/EMG interfaces. The amplifier has 90 dB CMRR and an offset voltage of 100 μ V.

A more modern choice is the INA333, which consumes 10 times less current, has 4 times lower input offset, and provides up to 100 dB CMRR at operating voltages from 1.8 V to 5.5 V.

It should be noted that both amplifiers require a path for the input bias current to operate correctly, even in DC measurements. The INA333 uses CMOS technology and requires approximately 70 pA of input current, allowing 20 M Ω input resistors to be placed without creating significant offset. For the AD623, this current is 17 nA since the amplifier uses bipolar transistors, and resistors are in the range of 1–10 M Ω to virtual ground. This is not noted by manufacturers of Open Hardware EEG systems, yet it is key to ensuring minimum functionality of the circuit in amateur use in home and heavily noisy environments.

The circuit uses 2 k Ω / 0.2 W input protection resistors, providing immunity up to approximately 20 V input voltage exceeding the 5 V supply. Similar resistors are used in the OpenEEG project. Additional protection is provided by BAV199 diodes at the inputs and outputs of the amplifiers connected to the patient. The device is not intended for medical use, and power supply isolation issues are resolved through wireless connectivity and battery power.

Active shield driving

Since inexpensive cables are used, a method of active shielding is applied to the cable braid, onto which the same potential extracted from the summing node of the instrumentation amplifiers' input signals is applied. This approach neutralizes the capacitance between individual conductors and the cable shield.

Most EEG practices use single unshielded wires to avoid the microphonic effect and signal attenuation from capacitance between the signal conductor and the cable braid. This manifests as large spikes when recording signals from the patient's head.

Since the presented module is designed for amateur use, active shield driving suppresses this effect. The active shield also prevents the triboelectric effect, which arises from friction of the insulation within the wire conductors. The circuit uses passive electrodes for simplicity of wiring, and because high-impedance electrodes are used, the cable would be extremely sensitive to any type of external capacitance. This further reduces requirements for contact gel when the

contact dries or undergoes microscopic displacement. The greatest influence of active shielding is on CMRR.

Suppression of radio frequency interference Fig. 5 shows an illustrative example of using an input capacitive filter to suppress radio frequency interference before the signal is applied to the instrumentation amplifier. [18].

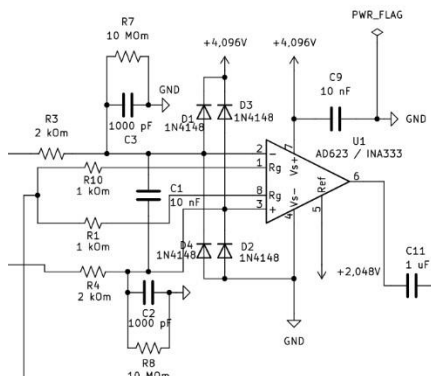


Fig.5 InAmp high-voltage clamping diodes and capacitive RF suppression protection

The selection of input capacitors requires that the capacitors from the two differential inputs to virtual ground be 10 times smaller in value than the main one. The selected components provide suppression of high-frequency radio interference at 77 kHz. Since capacitors with tolerance below 5% are difficult to order, manual selection of the most closely matched values is performed before assembly. This is done to ensure equal input amplitude-frequency characteristics across all channels.

When dealing with higher levels of interference, increasing the input capacitance is not recommended, as this leads to poor amplification of weak EEG gamma signals. [19]

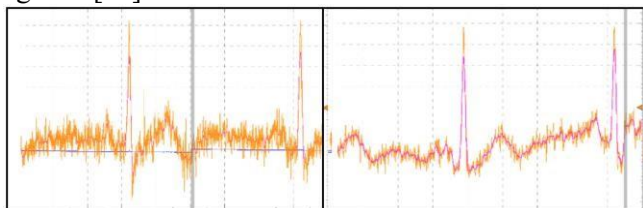


Fig.6 ECG signal in the presence of high radio frequency interference, respectively without and with filtering capacitors at the input.

Power supply interference

During experiments, a regular laptop was used, whose switching power supply is a source of high-frequency interference with broad spectrum and periodicity. Oscilloscope traces were captured from the +5 V regulator of the analog section with mains power

connected and disconnected. To prevent such interference from coupling into the precision instrumentation amplifiers and ADC module, a USB optical isolator and battery power supply are typically used. With a Wi-Fi connection, this is not necessary. (Fig.7)

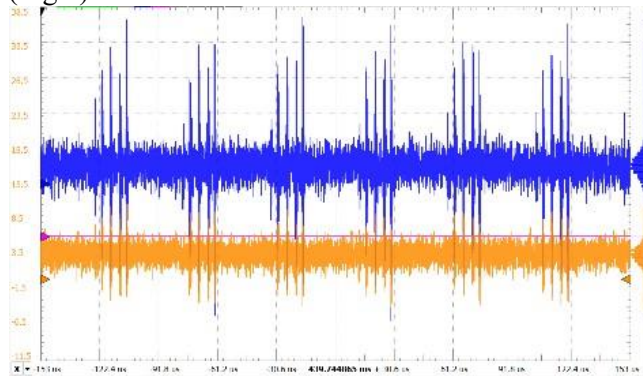


Fig.7 Typical switching computer power supply noise

Right leg drive (RLD)

A standard circuit is used for common-mode interference suppression in the patient, with the input isolated at DC, and a potentiometer can be placed in the feedback loop to set the gain in the range of 10–20 times. (Фиг.8)

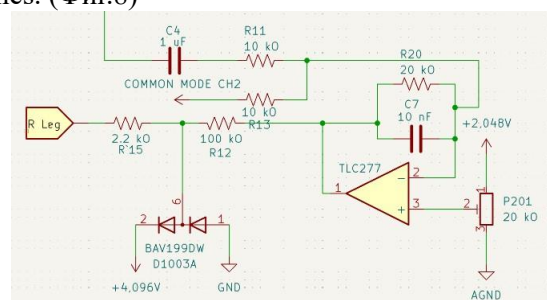


Fig.8 ECG/EEG Right Leg Drive Schematic

The role of this module in the circuit is to create an active Vref that causes the virtual ground of the measurement amplifier to "float" in common mode with the mains interference. The amplifier injects a counter-phase microcurrent into the patient via an additional electrode, attached to the right leg in ECG or to the ear in EEG. The feedback loop includes a 0.5–1 nF capacitor to suppress high-frequency noise.

Fig. 9 shows the 50/60 Hz common-mode input signal with distortions from a solar inverter and the counter-phase signal at the RLD driver output. Impulse interference from unbalanced inverters and switching power supplies is very difficult to remove from the useful signal. This seriously hinders the correct detection of EMG signals, and is especially problematic in the detection of EEG gamma waves.

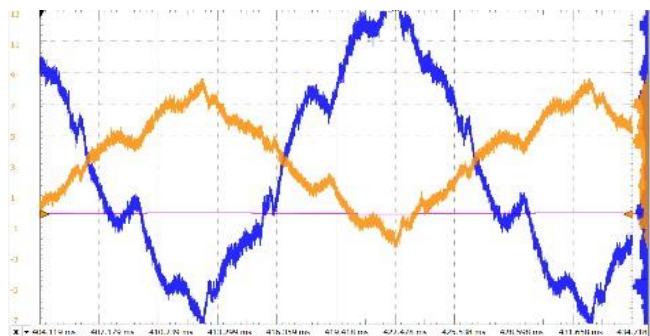


Fig.9 Common mode powerline noise and 50 Hz counterphase driver signal. Interference from solar inverters and air-conditioning is clearly visible.

Fig. 10 shows the effect of applying RLD, as well as randomly superimposed mains interference and interference from the laptop's switching power supply.

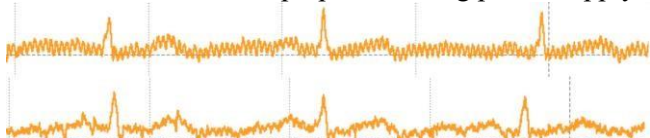


Fig.10 Powerline noise compensation without and with RLD. Muscle tremor is visible.

Data exchange protocol

The current implementation uses the EEG-SMT protocol, supporting up to 6 16-bit channels. The protocol stack includes: two synchronization bytes, protocol version, and packet sequence number used for detecting lost data. The data format is Big Endian (MSB first, followed by LSB). By default, the protocol operates at 57600 bps with a sampling frequency of 256 samples per second. The total packet length is 17 bytes and is sent every 3.91 milliseconds. The data format is 8 bits, 1 stop bit, no parity (8N1). The protocol is used in the following software: ElecGuru, OpenViBE, and BrainBay. A Bluetooth version also exists. This makes the protocol and module universal and convenient for integration with Python, C++, and Java programs. [20]

Similar commercial Open-Source products

The *EEG-SMT* module is manufactured by a Bulgarian company, with the design originating from the OpenEEG Project, which allows the creation of a modular measurement interface with up to 6 channels. [21] The module allows connection to a personal computer via serial interface or USB converter FT232RL. Implementations with up to 16 channels exist for this project. [7] The module uses the EEG-SMT protocol. [22]

OpenBCI Cyton represents the highest class among open-source platforms and uses specialized chips for precise 24-bit measurement of brain activity. [23] The system provides full access to raw data and is fully compatible with professional software for scientific analysis, making it a standard in the research community.

NeuroSky MindWave is a budget consumer device with a single channel, designed primarily for entertainment and basic meditation applications. It uses a closed architecture and a simplified interface that converts complex waves into ready-made concentration indicators, but its lack of resolution makes it unsuitable for serious work.

Emotiv EPOC is a designer wireless device with a fixed number of channels, distinguished by quick setup and a professional appearance for marketing purposes.

Backyard Brains SpikerBox is a simplified educational module created for school demonstrations of basic neurophysiology principles.

EEG processing software

Two software products are used for processing signals from the developed hardware — *OpenViBE* and *BrainBay*. (Table 1.)

Table 1

Comparison between *BrainBay* and *OpenViBE*

Feature	BrainBay	OpenViBE
Complexity	Low	High
Number of channels	Optimal up to 4–6	Unlimited (32+)
LSL support	Limited / via plugins	Native
Visualization (Topographic maps)	Basic	Professional
Processing	Linear	Parallel and matrix

BrainBay is lightweight, straightforward, and very intuitive for a small number of channels. Everything happens on a single screen view. Its extremely low resource consumption makes it fast and lightweight. It is convenient for quick hardware testing with biofeedback games. It is not suitable for managing many channels due to GUI limitations. It offers limited capabilities for complex signal filtering and does not support modern protocols such as LSL well.

OpenViBE is designed for professional scientific work and complex Brain-Computer Interfaces (BCI). The interface is split into two parts: Designer (where a

logical diagram is built with blocks) and Acquisition Server (for managing LSL and hardware connections). It supports 32+ channels without performance loss. It has built-in complex algorithms for real-time detection of P300 waves, motor imagery, and frequency analysis. It is considerably more complex to use. [24]

Testing and results

Extensive tests were carried out:

- Comparison of different instrumentation amplifiers (AD623 and INA333),
- Noise measurements and frequency response evaluation,
- ADC accuracy evaluation in different operating modes [25]
- WiFi communication and WebSocket visualization testing, [26] [27]
- BCI experiments with real users: cardiogram, "concentration", "blinking", motor imagery.

The project has achieved:

- A fully functional 8-channel mobile EEG module,
- 6–24-bit resolution across different versions,
- Stable and repeatable measurement of low-amplitude biopotentials,
- A precise calibration and machine learning process,
- A WiFi-based web interface for real-time visualization,
- Successful ECG, EOG, and EEG measurements. (Fig.11) [28]

The project's innovation manifests in several directions. First, the system uses entirely accessible and low-budget components for every part of the build — from the microcontroller and 16-bit ADC modules to the dry EEG electrodes and 3D-printed prototypes. This makes the development suitable for mass application and facilitates future expansion. The practical design, compatible with a headband without requiring implants, enhances safety, comfort, and the possibility of daily use both in laboratory and home environments.

The project is of significant social value, as it offers an alternative means of interaction with the digital environment for people with motor disabilities. By interpreting specific brainwave patterns as commands, the system can serve as a means of controlling games, software, or assistive devices. This opens new possibilities for inclusion, communication, and autonomy.

From an educational standpoint, the project demonstrates the power of open hardware (Arduino, ESP8266) and modern BCI technologies. It serves as a solid practical platform for training students and young engineers in the fields of biosignals, digital processing, and embedded systems. This contributes to the development of specialists in electronics, telecommunications, and medical technology.

The results obtained demonstrate successful processing of EEG signals with a multi-channel architecture, 16-bit resolution, stable operation of the analog stages, digital filtering, and reliable wireless communication via WiFi WebSockets. The prototype demonstrates real-time control of game actions via brain activity, confirming its applicability.

The potential for technological development is significant. Plans include expanding the system to an additional 8 channels (16 total), enabling more precise analysis of brain maps and control of more complex games or applications with more commands.

Introduction of machine learning for higher recognition accuracy is envisioned, as well as integration with other devices such as robotic systems or wheelchairs.

In its entirety, the project represents an accessible, socially significant, and highly innovative platform with great potential for development in medicine, rehabilitation, gaming, and education.

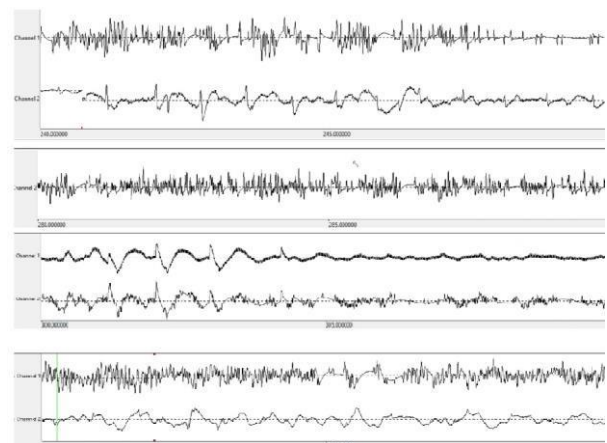


Fig.11 Different EEG signal readings in OpenViBE, captured from various points on the head

Conclusion

The project has high potential for real-world applicability in healthcare, education, rehabilitation, social services, and beyond. It is conceived for application in assisting people with motor impairments. Through the use of EEG signals, the system enables control of computers, software, or games without the

use of hands. This is important for users who cannot work with traditional interfaces such as a keyboard, mouse, or joystick. The technology has the potential to be extended to controlling wheelchairs, robotic assistants, and home automation systems, thereby supporting independence and quality of life.

The project also has educational value, serving as a practical platform for training students in electronics, biotechnology, signal processing, and artificial intelligence. Through the combination of hardware, software, and machine learning algorithms, it supports the development of young engineers and researchers, preparing them for the modern demands of industry.

In the entertainment industry, the project offers a new type of interaction — controlling video games and virtual environments through thought.

From an ecological and economic perspective, the system is architecturally built on modular, interchangeable components, ensuring repairability. It uses energy-efficient and readily available components. This reduces maintenance costs and enables wider deployment without a significant resource footprint.

Acknowledgment

The author would like to express sincere gratitude to the staff of CEEC for the opportunity to publish this work. This publication was made possible through the "Project of the Year" competition, organised by CEEC, in which the presented project was selected as the winning entry. The author is honoured by this recognition and thankful for the support and encouragement it represents.

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Received on: 30.04.2026

IoT-based indoor environmental monitoring and CO₂ prediction using FIWARE and Sigfox for smart laboratory environments

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This paper presents an Internet of Things-based system for continuous monitoring of carbon dioxide (CO₂), temperature, relative humidity, atmospheric pressure, and illuminance in a laboratory, together with a 15-min-ahead warning function for elevated CO₂ conditions. Sigfox-enabled sensors transmit measurements to ThingSpeak, while FIWARE Orion, QuantumLeap, CrateDB, and Grafana provide context management, time-series storage, and visualization. MATLAB retrieves the measurements, generates lagged CO₂ and recent-change features, and applies regression and ensemble classification models. Because high-CO₂ observations were infrequent, cost-sensitive learning and decision-threshold adjustment were employed. On the evaluated dataset, the threshold classifier achieved an accuracy of 62.63%, a precision of 0.09, a recall of 0.33, and an area under the receiver operating characteristic curve of 0.61. These results demonstrate the feasibility of the proposed end-to-end monitoring architecture, although the model exhibited only modest predictive discrimination. Consequently, larger and more diverse datasets are required before the model can be considered for automatic ventilation control.

Keywords – CO₂ prediction, FIWARE, indoor air quality, machine learning, Sigfox.

Introduction

Indoor environmental conditions affect occupant comfort, work performance, and laboratory safety. Carbon dioxide (CO₂) is commonly monitored as an indicator of occupancy-related ventilation conditions, although acceptable indoor air quality depends on multiple contaminants and building operational factors. Internet of Things (IoT)-based monitoring systems integrate multiple low-cost sensors, wireless communication, cloud storage, and visualization to provide continuous data at a finer temporal resolution than periodic manual measurements [1]. Ventilation design and operation should also be interpreted in accordance with current indoor air quality guidelines, such as ANSI/ASHRAE Standard 62.1-2025 [2].

Although monitoring provides information on current conditions, it does not offer advance warning of a rapid increase in CO₂ concentration. Short-term forecasting enables laboratory personnel to assess occupancy and ventilation conditions before a predefined operational threshold is exceeded. However, accurate forecasting is challenging because indoor CO₂ concentrations are influenced by occupancy, air

exchange, sensor noise, and sampling intervals, while high-CO₂ observations are typically much less frequent than normal observations.

This study develops an end-to-end monitoring and prediction framework that integrates Sigfox-enabled environmental sensors, ThingSpeak, FIWARE context management, time-series services, visualization, and MATLAB-based prediction. Rather than replacing a ventilation controller, the framework provides real-time monitoring and a 15-min-ahead decision-support signal that can be evaluated before implementing automatic control.

The main contributions of this study are as follows:

- an integrated IoT architecture for laboratory environmental monitoring;
- the use of lagged CO₂ and recent-change features for short-term prediction;
- cost-sensitive event classification and decision-threshold adjustment to address data imbalance; and
- a transparent evaluation based on precision, recall, the confusion matrix, and the receiver operating characteristic (ROC) curve.

Related work

Recent studies have combined indoor environmental sensing and machine learning for CO₂ forecasting. Kallio et al. compared regression and tree-based methods using a one-year office dataset and demonstrated the value of historical CO₂ and occupancy-related information [3]. Taheri and Razban compared several machine learning algorithms for demand-controlled ventilation and highlighted the relationship between prediction horizon and control performance [4]. Deep recurrent models have also been applied to IoT-enabled forecasting. Zhu et al. employed a long short-term memory (LSTM)-based approach [5], whereas Marquez-Zepeda et al. combined low-cost monitoring with short- and long-horizon CO₂ prediction [6].

The communication and data management layers are equally important for deployable systems. Low-power wide-area network technologies, such as Sigfox, enable long-range, low-power communication for sensor deployments, albeit with trade-offs in data rate, payload size, and network operation [7]. For indoor air quality applications, Anto et al. demonstrated a structured platform for collecting and managing heterogeneous data [8]. FIWARE Orion supports context updates, queries, and subscriptions [9], whereas ThingSpeak provides cloud-based data channels and MATLAB-integrated access to live data streams [10].

The present work differs from studies that focus solely on prediction models by evaluating an end-to-end framework encompassing sensing, context management, data storage, visualization, and operational warning generation. In addition, it explicitly examines the effects of class imbalance rather than relying solely on accuracy as a performance metric.

Methodology

System architecture

The proposed system comprises a sensing and data transmission pipeline, a prediction pipeline, and a FIWARE-based monitoring pipeline (Fig. 1). Sensor nodes measure CO₂ concentration, temperature, relative humidity, atmospheric pressure, and illuminance. The measurements are transmitted via the Sigfox network and backend to a ThingSpeak channel. MATLAB retrieves the channel data for feature generation, model inference, and estimation of the probability that the CO₂ concentration will exceed a predefined threshold 15 min ahead.

In parallel, a REST-based forwarding process

updates entities in the FIWARE Orion Context Broker. Orion maintains the latest context information and sends subscription notifications to QuantumLeap, which stores the time-series data in CrateDB. Grafana queries the stored data to generate monitoring dashboards. This architecture enables the prediction pipeline and the context management/time-series services to evolve independently while using the same sensor measurements.

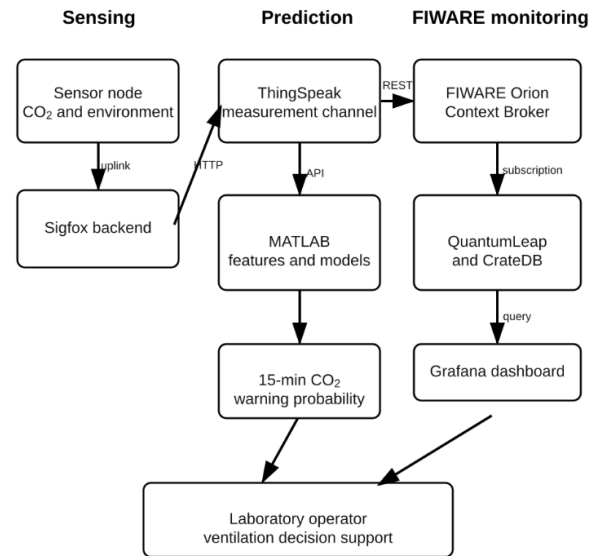


Fig.1. Architecture and data flow of the proposed monitoring and prediction system.

Data preparation and temporal features

The model inputs consist of the measured environmental variables. Sensor measurements are scaled in MATLAB before model training. To capture short-term temporal dynamics, the feature set includes lagged CO₂ values and the recent change in CO₂ concentration, calculated as the difference between consecutive measurements. These features characterize both the current CO₂ level and its temporal trend without requiring a complex physical model.

Prediction models

Two prediction formulations were evaluated. The regression formulation estimates the future CO₂ concentration using linear and ensemble regression models. The event-classification formulation predicts whether the CO₂ concentration 15 min ahead will exceed an application-defined operational threshold. Accordingly, the positive class represents a future high-CO₂ event, whereas the negative class represents a future CO₂ concentration at or below the threshold.

Because high-CO₂ events were infrequent in the evaluated dataset, cost-sensitive learning was used to increase the penalty for misclassifying positive

instances. The classifier output probability was subsequently converted into a class label using an operating threshold of 0.15. Lowering the operating threshold increases the number of warnings and may improve event detection but can also increase the false-alarm rate.

Evaluation procedure

The threshold classifier is evaluated using accuracy, precision, recall, and the area under the ROC curve (AUC). Precision represents the proportion of predicted high-CO₂ warnings that are correct, whereas recall represents the proportion of actual high-CO₂ events that are correctly identified. The confusion matrix is also reported because the evaluated dataset comprises 90 normal cases and only 9 high-CO₂ cases. Under this class imbalance, accuracy alone can obscure poor performance on the positive class.

Results and discussion

Table 1 summarizes the classifier performance at the selected probability threshold. The classifier achieved an accuracy of 62.63%, a precision of 0.09, a recall of 0.33, and an area under the AUC of 0.61. The AUC indicates modest discrimination between the two future threshold states, while the low precision suggests that most predicted high-CO₂ warnings were false positives.

Table 1

Performance of the threshold classifier.

Metric	Value
Accuracy	62.63%
Precision	0.09
Recall	0.33
ROC AUC	0.61
Probability threshold	0.15

The confusion matrix (Table 2) provides a more direct assessment of classifier performance. Of the nine high-CO₂ cases, three were correctly detected, whereas six were missed. Among the 90 normal cases, 59 were correctly classified and 31 were incorrectly identified as high-CO₂ events. Thus, the operating threshold of 0.15 increased sensitivity compared with a more conservative decision threshold, albeit at the cost of a high false-positive rate, making it less suitable for unattended automatic control.

Table 2

Confusion matrix at a probability threshold of 0.15.

	Predicted normal	Predicted high CO ₂
Actual normal	59	31
Actual high CO ₂	6	3

The ROC curve (Fig. 2) confirms that the model possesses some predictive capability, although its performance is insufficient to support direct ventilation actuation. Accordingly, the proposed platform is better regarded as a monitoring and decision-support prototype. Laboratory personnel can use the generated warnings in conjunction with dashboard history and current occupancy information to support operational decisions.

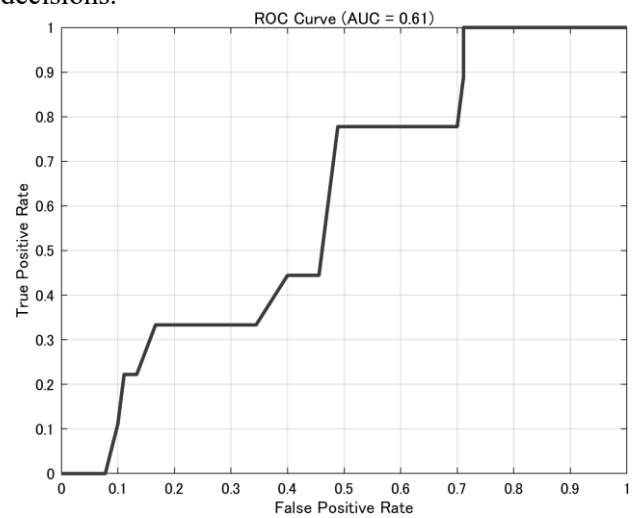


Fig. 2. ROC curve for the threshold classifier (AUC = 0.61).

The results also highlight the limitations of the current evaluation. The positive class comprises only nine cases, the dataset represents a single environment over a limited data-collection period, and no independent multi-site validation was performed. Although lagged and change-rate features provide temporal context, an ablation study is required to quantify the contribution of each feature. Furthermore, the regression analysis did not include a complete set of comparable error metrics; therefore, the present discussion focuses on the threshold classifier, for which the confusion matrix and ROC-based evaluation are available.

Conclusion

An IoT-based framework for indoor environmental monitoring and 15-min-ahead CO₂ warning was developed using Sigfox, ThingSpeak, FIWARE Orion, QuantumLeap, CrateDB, Grafana, and MATLAB. The proposed architecture provides an end-to-end pipeline from sensor data acquisition to context management,

time-series visualization, and predictive decision support.

At the selected operating threshold, the classifier detected three of the nine high-CO₂ events, achieving a precision of 0.09, a recall of 0.33, and an AUC of 0.61. These results demonstrate the technical feasibility of the proposed framework but also indicate that the current model is not suitable for autonomous ventilation control. Future work should increase the number and diversity of high-CO₂ observations, validate the system across multiple rooms and seasons, compare regression models using a comprehensive set of error metrics, perform feature ablation and probability calibration, and evaluate warning strategies with laboratory users.

Acknowledgements

The authors thank the provider of the environmental data used in this study. They also thank Enago for English-language editing and Altner Co., Ltd. for providing some of the IoT devices used in this research.

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Received on: 16.05.2026

26 – 27 November 2026
National Science and Technical Centre,
108 Rakovsky St., Sofia

ЕЛЕКТРОТЕХНИКА И ЕЛЕКТРОНИКА Е+Е

61 год. 1-2/2026

Научно-техническо списание

Издание на: Съюза по електроника, електротехника и съобщения /СЕЕС/

Главен редактор:

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ISSN 0861-4717

eISSN 2603-5421 Online

СЪДЪРЖАНИЕ

Станислав Иванов

Обемна визуализация на производителност на радиовръзките, мониторинг на аномалии и метеорологично затихване в съвременните мобилни мрежи

1

Ерман М. Гелдиев

Мултимоделна консенсусна рамка за откриване на пневмония: оптимизиране на диагностичната чувствителност при ограничения на „Зелен изкуствен интелект“

8

Ванеса С. Назъкова

Проектиране и хардуерна оптимизация на модулна ЕЕГ система за изграждане на приложения, използващи мозъчно-компютърен интерфейс

19

Takeshi Tanaka, Tomoo Sigehuzi, Masayuki Yamauchi, Shuji Oji, Masaya Watanabe, Satoru Tada, Koji Kakugawa, Katia Vutova

IoT-based indoor environmental monitoring and CO2 prediction using FIWARE and Sigfox for smart laboratory environments

28



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