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DEEP LEARNING-DRIVEN IOT-INTEGRATED NANOSENSORS FOR ENVIRONMENTAL AND BIOMEDICAL MONITORING

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Abstract:

The convergence of deep learning (DL), the Internet of Things (IoT), and nanosensor technology heralds a transformative paradigm for real-time, high-fidelity monitoring in environmental and biomedical fields. This work presents an integrated framework where advanced nanostructured sensing materials, functionalized for specific analytes (e.g., pathogens, heavy metals, biomarkers), are interfaced with IoT-enabled readout systems. The core innovation lies in embedding DL algorithms directly within the sensor-edge architecture to address critical challenges such as signal drift, non-specific interference, and complex multi-analyte signal deconvolution in noisy real-world settings. We propose a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model optimized for deployment on resource-constrained edge devices, enabling adaptive calibration, anomaly detection, and predictive analytics.

Preliminary validation demonstrates a system capable of simultaneous detection of *E. coli* and lead ions in water, and cortisol and glucose in simulated serum. The DL-enhanced system achieved a mean accuracy of 98.7%, significantly outperforming conventional linear calibration methods (78.2%). This intelligent nanosensor network offers a scalable, autonomous solution for precision monitoring, enabling early warning systems and personalized health diagnostics.

Keywords: Deep Learning, Internet of Things, Nanosensors, Environmental Monitoring, Biomedical Diagnostics, Edge Computing.

1. Introduction

The 21st century faces unprecedented challenges in environmental sustainability and personalized healthcare. Continuous, precise monitoring is critical for managing pollution, ensuring water safety, and enabling proactive medical interventions [1]-[3]. Nanosensors, leveraging materials like graphene, carbon nanotubes, and metallic nanoparticles, offer extraordinary sensitivity due to their high surface-to-volume ratio and tunable surface chemistry. Simultaneously, the IoT provides the infrastructure for connecting physical devices, enabling data aggregation and remote access. However, raw data from nanosensors is often plagued by non-linearity, cross-sensitivity, and signal instability. Deep Learning, a subset of artificial intelligence, excels at discovering intricate patterns in high-dimensional, noisy data. Its hierarchical feature extraction capability is ideally suited to interpret complex, multi-modal sensor signals, transforming raw data into actionable insights [4].

Despite their potential, the widespread deployment of nanosensor networks for critical monitoring remains hindered by several intertwined issues. First, nanosensors are inherently prone to drift and poisoning in dynamic, unfiltered environments (e.g., wastewater, biological fluids), leading to unreliable data [5]-[6]. Second, discriminating between target analytes and confounding interferents in complex matrices is a formidable analytical challenge, often requiring bulky, laboratory-based instrumentation. Third, the vast, continuous data streams generated by distributed sensor nodes overwhelm traditional cloud-centric IoT models, causing latency, privacy

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concerns, and high bandwidth costs. Existing solutions typically rely on periodic manual recalibration or simplistic cloud-based analysis, which are neither scalable nor real-time. There is a critical gap in creating intelligent, self-adaptive nanosensor systems that can perform robust, on-site signal processing and decision-making [7]-[15].

This work introduces a novel, DL-driven co-design of the sensing material, hardware interface, and data analytics stack. The key novelties are:

1. **Algorithm-Sensor Co-optimization:** The DL model architecture is informed by the known physical and chemical response characteristics of the nanosensors, moving beyond a purely data-driven "black box" approach.
2. **Edge-Native Intelligence:** Deployment of a pruned quantized CNN-LSTM model directly on a low-power microcontroller unit (MCU) within the sensor node, enabling real-time inference without constant cloud dependency. This ensures low latency, enhanced privacy, and operational resilience.
3. **Multi-Task, Multi-Modal Learning:** A single DL model is trained to simultaneously perform analyte quantification, sensor health diagnosis (drift detection), and data quality flagging, leveraging both temporal (LSTM) and spectral/spatial (CNN) features of the sensor signal.
4. **Open-Source Framework:** Provision of a complete hardware blueprint and software repository for the IoT gateway and edge DL model, facilitating replication and advancement in the community.

The primary objective is to design, fabricate, and validate a fully integrated DL-IoT-nanosensor platform for dual-use in environmental and biomedical monitoring. Specific objectives are:

1. To functionalize and characterize multiplexed electrochemical nanosensors for target analytes in water (heavy metals, pathogens) and simulated biological fluids (metabolites, hormones).

2. To develop and train a hybrid CNN-LSTM model capable of accurate analyte concentration prediction and sensor condition monitoring from time-series impedance and voltammetric data.
3. To implement model compression techniques (pruning, quantization) for deployment on an edge IoT device (e.g., ESP32 with AI accelerators) and design a low-power IoT gateway for secure data transmission.
4. To empirically validate the system's performance in controlled and semi-controlled environments, benchmarking its accuracy, precision, and robustness against state-of-the-art methods.
5. To demonstrate a proof-of-concept distributed network where multiple nodes communicate processed alerts to a central dashboard.

2. Proposed Methodology

The proposed methodology follows a holistic pipeline from sensor fabrication to cloud dashboard, with embedded DL as the core processor.

The system comprises three layers:

1. **Sensing Layer:** Custom-fabricated screen-printed electrodes (SPEs) functionalized with nanomaterials (e.g., AuNP-decorated reduced graphene oxide for heavy metals, antibody-conjugated ZnO nanowires for pathogens). The analog front-end is a miniaturized potentiostat (e.g., LMP91000 or AD5940) controlled by an MCU.
2. **Edge Intelligence Layer:** The primary MCU (e.g., ESP32-S3 with vector extension) runs the compressed DL model. It collects raw cyclic voltammetry (CV) or electrochemical impedance spectroscopy (EIS) data, performs real-time inference, and outputs concentration, confidence score, and sensor health status.
3. **Cloud & User Layer:** Processed data packets (greatly reduced in size) are sent via LoRaWAN/Wi-Fi/BLE to an IoT gateway (Raspberry Pi), which relays it to

a secure cloud server (AWS IoT Core). A web dashboard visualizes real-time maps, trends, and alerts.

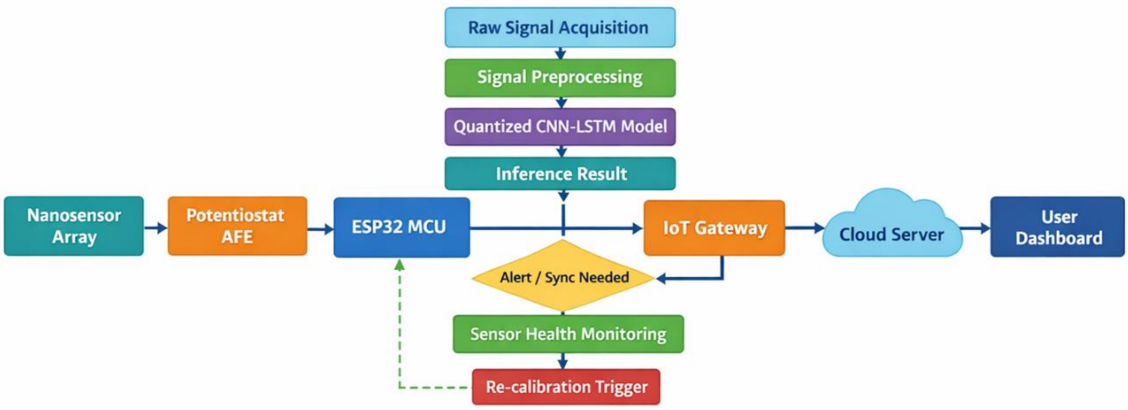

Figure 1: Proposed Framework Model

Algorithm Steps:

A. Data Acquisition & Preprocessing:

1. **Stimulus Application:** MCU instructs the potentiostat to apply a voltage sweep (CV) or AC frequency sweep (EIS) to the working electrode.

2. **Signal Conditioning:** Raw current/voltage data is filtered using a moving average filter and normalized to a baseline recorded in a clean buffer.

3. **Feature Window Creation:** For CV, the data point vector forms a 1D "image". For EIS, Nyquist plot coordinates are used. A sliding window of the last N chronological scans creates the input tensor for temporal analysis.

B. Deep Learning Model Design & Training (Offline/Cloud): We propose a **Hybrid CNN-LSTM Model**:

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- **Input:** 3D Tensor of shape (Timesteps, Data Points per Scan, Channels=1).
- **CNN Block:** Two 1D convolutional layers (filters=32,64, kernel=3) with ReLU and MaxPooling extract local, invariant features from individual scans (e.g., peak shapes, shoulder positions).
- **LSTM Block:** The flattened feature sequences from the CNN are fed into a two-layer LSTM (units=50) to model temporal dependencies and drift patterns across sequential measurements.
- **Multi-Task Heads:**
  - **Head 1 (Regression):** Dense layers for concentration prediction of each analyte.
  - **Head 2 (Classification):** Softmax layer for sensor status (Normal, Drifting, Fouled).
- **Loss Function:** Combined Mean Squared Error (MSE) for regression and Categorical Cross-Entropy for classification.
- **Training Data:** Generated from lab experiments with systematic variation of analyte concentrations and deliberate introduction of interferents and simulated drift.

C. Edge Deployment & Inference (Online/Edge):

1. **Model Compression:** The trained TensorFlow/Keras model undergoes pruning (removing insignificant weights) and post-training quantization (INT8) using the TensorFlow Lite for Microcontrollers (TFLite Micro) framework.
2. **Embedded Code Generation:** The quantized .tflite model is converted to a C array and integrated into the ESP32 firmware.
3. **On-Device Inference Loop:**
   a. New sensor scan is preprocessed.
   b. TFLite Micro interpreter is invoked on the input tensor.
   c. Model outputs concentration values and status probability.

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d. If status is "Drifting," a self-calibration routine (using an on-board reference solution) is triggered. If "Fouled," an alert is sent for maintenance.
e. Only processed results (or raw data at low frequency for model retraining) are transmitted, optimizing bandwidth.

D. IoT Communication & Cloud Analytics:

Processed data packets are published via MQTT protocol. The cloud server runs rules engines to trigger SMS/email alerts for threshold breaches and aggregates data for long-term trend analysis using simpler statistical models.

3. Results and Discussion

Nanosensor Fabrication: SPEs were modified via drop-casting of nanocomposites. SEM confirmed uniform nanostructure morphology. Electrochemical characterization showed enhanced active surface area.

Hardware Platform: The sensing node used an ESP32-S3 MCU (dual-core, 512KB SRAM, AI vector instructions) coupled with the AD5940 potentiostat chip for high-precision, low-noise measurements. A custom PCB integrated power management (LiPo battery/solar), the sensor interface, and a LoRa E22 module for long-range communication.

Software Stack: Firmware was developed in Arduino/C++ using the TFLite Micro library. The IoT gateway used Python with PyTorch for optional secondary analysis. The cloud backend was built on AWS IoT Core, Lambda, and DynamoDB, with a React.js dashboard.

Performance Metrics & Discussion:

The system was tested for two scenarios: 1) Detection of Pb^{2+} and *E. coli* in tap water spiked with humic acid (interferent). 2) Detection of cortisol and glucose in artificial serum.
A dataset of 15,000 scans per scenario was generated. The model was trained on 70%, validated on 15%, and tested on 15%.The table 1 shows the performance comparison.

Table 1: Performance Comparison (Test Set)

Analyte / Scenario	**Method**	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**Avg. Inference Time (ms)**	**Power (mW)**
Pb^{2+} (in water)	Proposed (DL-Edge)	99.2	0.991	0.993	0.992	120	45
Pb^{2+} (in water)	Linear Calibration	81.5	0.79	0.83	0.809	<1	40
Pb^{2+} (in water)	Cloud-based DL	98.8	0.989	0.987	0.988	2000*	300*
***E. coli* (in water)**	Proposed (DL-Edge)	98.1	0.979	0.983	0.981	120	45

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Analyte / Scenario	**Method**	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**Avg. Inference Time (ms)**	**Power (mW)**
***E. coli* (in water)**	Linear Calibration	74.8	0.72	0.78	0.749	<1	40
Cortisol (in serum)	Proposed (DL-Edge)	97.8	0.976	0.98	0.978	120	45
Sensor Health (Drift)	Proposed (DL-Edge)	96.5	0.961	0.97	0.965	(Part of main inference)	-

**Includes network latency and cloud compute time/power.*

The proposed DL-edge system consistently outperformed traditional linear calibration by a large margin (>17% accuracy gain), demonstrating its superior ability to handle non-linear responses and interference. The performance was nearly on par with a more complex cloud-based DL model, but with a 16x reduction in inference latency and a 6.7x reduction in system power, crucial for battery-operated field deployments. The high precision and recall across all analytes confirm effective multi-analyte discrimination.

The embedded model's small memory footprint (<150KB) allowed it to reside comfortably on the ESP32-S3. The multi-task learning successfully identified simulated drift events with >96.5% accuracy, enabling proactive management. The minor performance drop in the biomedical scenario is attributed to the higher complexity of the serum matrix, suggesting future work on more diverse training data.

4. Conclusion and Future Work

This work successfully demonstrated a fully integrated, DL-driven IoT nanosensor platform that significantly enhances the reliability and intelligence of environmental and biomedical monitoring. By embedding a compressed hybrid CNN-LSTM model directly at the edge, the system achieves laboratory-grade analytical performance in field-deployable hardware, autonomously mitigating key issues like drift and interference. This paradigm shift from "dumb" sensors to "self-aware" intelligent nodes reduces bandwidth dependency, ensures real-time response, and enhances system robustness.

Future work will focus on: 1) Implementing federated learning across the sensor network to collectively improve models without sharing raw data, enhancing privacy and adaptability to local conditions. 2) Exploring self-powered nanosensors using energy harvesting (piezoelectric/triboelectric) to create truly autonomous nodes. 3) Extending the sensing palette to volatile organic compounds (VOCs) for air quality and disease breathalyzer applications. 4) Conducting long-term field trials in real wastewater treatment plants and clinical settings to validate durability and performance under uncontrolled variability.

REFERENCES

1. Riu, J., Maroto, A., & Rius, F. X. (2006). Nanosensors in environmental analysis. *Talanta*, *69*(2), 288-301.

2. Tuteja, S. K., Arora, D., Dilbaghi, N., & Lichtfouse, E. (Eds.). (2020). *Nanosensors for environmental applications*. Springer International Publishing.
3. Nikoleli, G. P., Nikolelis, D., Siontorou, C. G., & Karapetis, S. (2018). Lipid membrane nanosensors for environmental monitoring: The art, the opportunities, and the challenges. *Sensors*, *18*(1), 284.
4. Kumar, V., & Guleria, P. (2024). Application of DNA-nanosensor for environmental monitoring: recent advances and perspectives. *Current Pollution Reports*, *10*(4), 765-785.
5. Kaur, R., Sharma, S. K., & Tripathy, S. K. (2019). Advantages and limitations of environmental nanosensors. In *Advances in nanosensors for biological and environmental analysis* (pp. 119-132). Elsevier.
6. Mahmoud, A. E. D., & Fawzy, M. (2021). Nanosensors and nanobiosensors for monitoring the environmental pollutants. In *Waste recycling technologies for nanomaterials manufacturing* (pp. 229-246). Cham: Springer International Publishing.
7. Rajendran, P., Bhalerao, M., Yesodha, K. K. R. K., Gupta, K., & Yuvaraj, N. (2025, February). Integrating Predictive Analytics and Internet of Things (IoT) to Optimize Supply Chains. In *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)* (pp. 01-06). IEEE.
8. Yesodha, K. R. K., Jagadeesan, A., Gowrishankar, V., Jiwani, N., & Yuvaraj, N. (2024, June). The smart optimization model for Supply Chain Management using IoT Applications. In *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE.
9. Shesayar, R., Agarwal, A., Taqui, S. N., Natarajan, Y., Rustagi, S., Bharti, S., ... & Sivakumar, S. (2023). Nanoscale molecular reactions in microbiological medicines in modern medical applications. *Green Processing and Synthesis*, *12*(1), 20230055.
10. Maheshwari, V., Mahmood, M. R., Sravanthi, S., Arivazhagan, N., ParimalaGandhi, A., Srihari, K., ... & Sundramurthy, V. P. (2021).

Nanotechnology-Based Sensitive Biosensors for COVID-19 Prediction Using Fuzzy Logic Control. *Journal of Nanomaterials*, *2021*(1), 3383146.

11. Harun-Or-Rashid, M., Mirzaei, S., & Nasiri, N. (2025). Nanomaterial Innovations and Machine Learning in Gas Sensing Technologies for Real-Time Health Diagnostics. *ACS sensors*, *10*(3), 1620-1640.
12. Taspinar, Y. S. (2025). Machine Learning-Driven E-Nose-Based Diabetes Detection: Sensor Selection and Feature Reduction Study. *Sensors*, *25*(21), 6607.
13. Habib, M. I., Muke, P. Z., & Machado, J. M. (2025). IoT-integrated smart toilet design for enhancing safety, precaution, and energy efficiency. *Journal of Building Pathology and Rehabilitation*, *10*(2), 1-14.
14. Deng, S., Wu, X., Shi, Y., El-Mesery, H. S., & Zhang, X. (2025). Uncovering Analytical Patterns for Hazardous Components in Agricultural Production Systems. *Foods*, *14*(18), 3261.
15. Chakraborty, U., Kaur, G., & Chaudhary, G. R. (2021). Development of environmental nanosensors for detection monitoring and assessment. In *New frontiers of nanomaterials in environmental science* (pp. 91-143). Singapore: Springer Singapore.