AI for Environmental, Energy, and IoT Applications: UniCas Industrial Research Highlights

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Abstract

Artificial Intelligence (AI) is reshaping industrial processes by enabling accurate, scalable, and domain-specific solutions. This paper presents four AI-driven methodologies applied to diverse industrial scenarios. First, a deep learning framework based on RetinaNet and InceptionV3 achieves a recall of 91.5% in detecting illegal microdumps from very high-resolution satellite imagery, enhancing automated environmental monitoring. Second, side-channel electromagnetic emissions and current absorption from IoT devices are analyzed using machine learning classifiers—Logistic Regression, SVM, and CNN+LSTM—reaching up to 98.32% accuracy in application profiling, with implications for cybersecurity. Third, a novel Electrochemical Impedance Spectroscopy (EIS) dataset from lithium iron (LFP) batteries is used to train machine learning models for State-of-Charge (SoC) classification, achieving 89% accuracy with Support Vector Machines. Finally, a deep learning system combining a low-cost SENSIPLUS sensor and a CNN achieves 95.78% average accuracy in classifying eight water pollutants from time-series impedance data. These results confirm the effectiveness of AI and deep learning—including convolutional and recurrent neural networks—for addressing complex challenges in environmental monitoring, battery diagnostics, and IoT security.

Keywords

Artificial Intelligence, Deep Learning, Remote Sensing, Water Quality Monitoring, IoT Security, Electrochemical Impedance Spectroscopy

1. Introduction

Artificial Intelligence (AI) is a key driver of Industry 4.0, enabling data-driven innovation in manufacturing, infrastructure, and energy [1]. In particular, machine learning (ML) and deep learning offer powerful tools to extract patterns from data, improving accuracy and decision-making over traditional approaches [2].

This paper presents four industrial applications that leverage ML/DL techniques and domain-specific datasets.

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The first focuses on detecting illegal microdumps from high-resolution satellite imagery. Marrocco et al. [3] developed a framework combining RetinaNet and InceptionV3, achieving a 90% detection rate in the Campania region using multispectral data.

The second addresses cybersecurity in IoT. Rega et al. [4] demonstrated how ML can classify running applications via side-channel data (e.g., power and EM emissions), highlighting implications for system profiling in industrial IoT.

The third concerns battery management. Mustafa et al. [5] provided an EIS-based dataset from lithium iron phosphate cells at various charge levels, enabling deep models to estimate the State-of-Charge (SoC) with improved accuracy.

The fourth involves water quality monitoring. Mustafa et al. [6] proposed a CNN-based system using Sensichips Smart Water Cable Sensor data, achieving 95.78% accuracy in detecting water-soluble pollutants.

The remainder of this paper is organized as follows: Section 2 details microdump detection from satellite imagery [3]; Section 3 discusses side-channel analysis for IoT [4]; Section 4 covers EIS-based SoC estimation [5]; Section 5 describes water pollution detection [6]; Section 6 concludes with a synthesis and future directions.

2. Microdump Detection from Satellite Imagery

This section summarizes the main elements of the research aimed at addressing the environmental challenge of illegal microdump detection from very high-resolution (VHR) optical satellite imagery using deep learning techniques, as detailed in [3]. The research specifically targets the Campania region in Italy, an area significantly impacted by illegal waste dumping, exacerbated by historical waste management crises.

2.1. Context and Problem Statement

Illegal dumping, particularly microdumps, poses a substantial threat to environmental health and safety. Microdumps are typically small-scale illegal waste disposal sites, varying in size from a few square meters to tens or even hundreds of square meters, primarily located in peri-urban and rural areas. These sites not only contaminate local environments but can also lead to severe ecological and health issues.

Traditional surveillance methods rely heavily on manual inspection and photointerpretation, which are time-consuming and costly. The proposed research exploits automated image analysis methodologies to detect microdumps more efficiently, allowing for improved resource allocation and more targeted interventions by environmental protection agencies.

2.2. Satellite Data and Preprocessing

Satellite images from the Pleiades and GeoEye-1 missions were utilized due to their high spatial resolution capabilities, providing ground sampling distances of 0.50 m and 0.40 m per pixel, respectively. Preprocessing involved converting original 16-bit images to 8-bit using histogram stretching to enhance the images' visual clarity and analytical effectiveness. Such preprocessing steps are critical to ensure compatibility and effectiveness of subsequent deep learning models.

2.3. Methodological Framework

The detection framework comprises two integrated neural network modules:

- **RetinaNet Object Detection (OD)**: RetinaNet, known for its effective object detection capabilities in remote sensing applications, was employed to initially identify and localize regions potentially containing microdumps. RetinaNet uses a ResNet50 backbone combined with a Feature Pyramid Network (FPN), providing robust multi-scale feature extraction.

- **InceptionV3 Pixel-Wise Classification (PWC)**: This network, initially pre-trained on the large-scale ImageNet dataset, was fine-tuned specifically for microdump detection. It offers pixel-level classification to refine detections and improve the precision of the identified regions.
- **Fusion Rule**: A fusion algorithm combines the outputs of both RetinaNet and InceptionV3 models. This integrated approach reduces false positives, leveraging the strengths of both network architectures to yield more accurate detections.

2.4. Experimental Setup and Results

The experimental evaluation was carried out using imagery collected over a 25 km^2 region north of Naples, encompassing the municipalities of Acerra, Caivano, and Afragola. The dataset for training and testing involved a comprehensive ground truth obtained from manual photointerpretation processes. The dataset included thousands of manually annotated patches and bounding boxes that ensured robust training and validation phases.

Experimental results demonstrated the model's capability, with average precision and recall values initially recorded at approximately 74.54% and 47.86%, respectively. To address recall limitations, an ensemble of six independently trained models was deployed. This ensemble strategy markedly enhanced recall to 91.50%, though with a consequent reduction in precision to 58.76%.

The trade-off significantly improves the probability of detecting actual microdump sites, which is particularly beneficial for end-user scenarios where missing a dumping site carries high environmental and economic costs.

3. Side-Channel Analysis and Machine Learning

This section summarizes the primary elements of research that combines side-channel analysis and machine learning to classify running applications on connected devices, as presented in [?]. The research focuses specifically on cybersecurity threats to IoT (Internet of Things) environments, exploiting side-channel information such as electromagnetic emissions to identify active processes.

3.1. Context and Problem Statement

The reconnaissance phase of cyber-attacks traditionally involves network scanning and exploitation of software vulnerabilities. Side-channel attacks, typically targeting cryptographic operations through power consumption or electromagnetic emissions, present a novel cybersecurity threat when exploited to profile running applications, particularly on IoT devices.

3.2. Data Acquisition and Experimental Setup

The experiment involved a Raspberry Pi 4 Model B as the device under test (DUT), chosen for its popularity in IoT applications. Electromagnetic emissions were captured using a TiePie HS6 oscilloscope and a TS-Lindgren magnetic field probe, sampling at 1 MS/s over 40 seconds per scenario. Four application scenarios—two web browsers and two email clients—were tested to assess the classifier's ability to discriminate between similar processes.

3.3. Feature Extraction and Classification Methodology

A rigorous preprocessing protocol was implemented, involving transient elimination, RMS signal computation, downsampling, and robust scaling. Time and frequency domain features were extracted, such as mean, standard deviation, skewness, kurtosis, and spectral features derived from FFT.

Various classifiers were evaluated, including Logistic Regression, Support Vector Machines (SVM), Random Forest, and a deep learning model combining CNN and LSTM networks with attention mechanisms.

3.4. Experimental Results and Implications

Logistic Regression achieved the highest accuracy (98.32%), followed closely by SVM (97.50%) and CNN+LSTM (97.22%). Simpler methods outperformed complex neural architectures in this context, suggesting that robust side-channel information extraction and simpler classifiers are highly effective for practical IoT cybersecurity applications.

This research highlights potential privacy risks and the necessity for robust cybersecurity measures in IoT deployments. Future research directions include developing transfer learning methods, enhancing hardware-independent feature extraction, and optimizing lightweight models suitable for IoT devices.

4. EIS-Based Lithium LFP Battery Dataset for Data-Driven SoC Estimation

This section presents the dataset developed for data-driven State of Charge (SoC) estimation using Electrochemical Impedance Spectroscopy (EIS) on Lithium Iron Phosphate (LFP) batteries. Accurate SoC estimation plays a critical role in the reliable operation of battery management systems (BMS), particularly for lithium-ion batteries deployed in electric mobility, consumer electronics, and stationary storage. LFP batteries are increasingly preferred for such applications due to their chemical and thermal stability, long cycle life, and lower material costs. EIS provides a non-invasive method for capturing the internal dynamics of battery cells across a wide range of frequencies, offering valuable insights into diffusion behavior, charge transfer resistance, and interfacial phenomena. The dataset described here is designed to support machine learning applications and electrochemical analysis for robust and accurate SoC modeling.

4.1. Dataset Description

The dataset comprises Electrochemical Impedance Spectroscopy (EIS) measurements collected from eleven commercial 600 mAh Lithium Iron Phosphate (LFP) battery cells (model IFR14500EC). Each cell was tested at 20 discrete State of Charge (SoC) levels, ranging from 5% to 100% in 5% increments. At each SoC point, impedance was measured across 28 frequencies ranging from 0.01 Hz to 1 kHz. All experiments were conducted in a climate-controlled chamber maintained at 20 °C using a Hioki BT4560 impedance analyzer in conjunction with a Zketech EBD-A20H electronic load. A four-terminal configuration was employed to minimize the influence of contact and cable resistance.

To enhance the dataset's diversity, batteries were sourced from different manufacturing batches. Each battery underwent two full discharge cycles, and all data were saved in CSV format to facilitate integration into machine learning workflows and electrochemical modeling pipelines.

Robust validation procedures were applied to ensure the integrity and consistency of the measurements. Nyquist plots were analyzed for each SoC level to visually inspect impedance behavior and identify any anomalies. In addition, the Lin–Kramers–Kronig (Lin-KK) relations were applied to assess the linearity, causality, and stability of the EIS data. Relative fitting errors between measured and modeled impedance values remained below 0.3%, confirming high measurement fidelity. These validation steps establish the dataset's suitability for both physics-based modeling and data-driven analysis approaches.

4.2. Data-Driven SoC Estimation Using Machine Learning and Image-Based Deep Learning

To assess the dataset's suitability for data-driven SoC modeling, we performed classification experiments using Support Vector Machines (SVM). Real and imaginary parts of the impedance spectra were used as input to classify SoC into 10 discrete 10% intervals. The SVM model achieved 89% accuracy, confirming the effectiveness of impedance features for supervised SoC estimation.

The dataset offers a solid basis for developing and benchmarking data-driven SoC estimation methods using EIS data. Its design supports various machine learning models for both research and practical battery diagnostics. However, its scope is currently limited to eleven LFP cells and two discharge cycles under fixed temperature, which may affect generalizability. Future work will extend the dataset with more cells, cycles, and variable conditions, and explore advanced architectures and real-time validation in embedded systems.

5. Detection of Water Pollutants with Deep Learning and Smart Sensors

This section summarizes a deep learning-based methodology for the classification of water pollutants using data acquired through the SENSIPLUS smart microsensor, as presented in [?]. The proposed system combines a low-cost, IoT-ready hardware infrastructure with an advanced deep learning model to identify common water pollutants in real time.

5.1. System Overview and Dataset Acquisition

The Sensichips Smart Cable Water (SCW) system, based on the SENSIPLUS chip, was employed for data acquisition. This chip utilizes Electrical Impedance Spectroscopy (EIS) across a wide frequency range (3.1 MHz to 1.2 MHz) to detect water-soluble pollutants using InterDigitated Electrodes (IDEs) metalized with various materials (gold, platinum, silver, copper, palladium, nickel).

Eight pollutant classes were monitored: Acetic Acid, Ammonia, Hydrogen Peroxide, Hydrochloric Acid, Phosphoric Acid, Sodium Chloride, Sodium Hydroxide, and Sodium Hypochlorite. For each pollutant, 1,600 samples were collected after a stabilization phase of 600 samples with potable water. Impedance values from gold, platinum, silver, and nickel IDEs were used to build 10-dimensional feature vectors.

5.2. Preprocessing and Feature Extraction

Preprocessing steps included the computation of Exponential Moving Averages (EMA) and their differences (EMA-D) to highlight temporal variations. A sliding window of size 32 (stride 1) was applied to the EMA-D data to create overlapping sequences for input into the classifier. Only the stable part of each signal (after discarding the first 400 samples) was used.

5.3. Classification Models and Architecture

Three neural network models were tested: Simple RNN, LSTM, and a deep Convolutional Neural Network (CNN). The CNN model used a 32x10 input tensor derived from the sliding window and consisted of several convolutional layers with ReLU activations, batch normalization, dropout regularization, and dense layers for final classification.

5.4. Experimental Results

The performance of the classifiers was evaluated using 10-fold cross-validation. CNN achieved the highest average accuracy of 95.78%, with a maximum accuracy of 99.60% in Fold-4. LSTM followed with 93.66% and RNN with 85.28%.

The high performance of the CNN model demonstrates the feasibility of low-cost, deep learning-enabled pollutant classification from impedance spectra acquired with SENSIPLUS. The ability to accurately detect pollutants like acids, peroxides, and chlorides in real-time makes this approach suitable for deployment in environmental monitoring systems.

Future work will focus on extending the system to handle more pollutant classes, improving performance in transient signal conditions, and exploring ConvLSTM and ensemble architectures for further robustness.

6. Synthesis and Future Directions

The four use cases presented in this work demonstrate the versatility and impact of Artificial Intelligence (AI) in addressing complex industrial challenges across environmental monitoring, energy diagnostics, and cybersecurity. Each domain benefits from tailored machine and deep learning architectures, trained on carefully curated datasets, and optimized for operational constraints specific to industrial applications.

These results point to several promising directions for future research. One is enhancing model generalization and transferability across devices, acquisition conditions, or geographical regions, for example through transfer learning or domain adaptation. Another is enabling real-time and embedded deployment of models by reducing inference latency and optimizing energy efficiency, which is crucial for edge computing platforms and microcontrollers. Integrating multimodal information—combining spatial, spectral, and temporal features—could improve predictive accuracy and context awareness. Finally, explainability and trust are essential in high-stakes industrial scenarios; adopting explainable AI (XAI) techniques can support transparency and human-in-the-loop decision-making.

In summary, the presented AI frameworks offer both methodological advancements and practical implementations, showing how intelligent systems can contribute to sustainability, reliability, and security in modern industrial ecosystems.

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Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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