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Real-Time Classification of Power Quality Disturbances using 1D CNN on Raw Signal: Noise Robustness and Monitoring into a Small City

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INTRODUCTION & AIM

The paper proposes a paradigm shift in modern power grid monitoring, migrating from complex analyses conducted in the Cloud to instantaneous decisions taken directly at the "edge" of the network (Edge Computing). In an energy context marked by the instability of renewable sources, the main goal is the ultra-fast and precise identification of faults to prevent damage to critical infrastructure. The central objective is to develop an automatic real-time classification system that eliminates Cloud latencies and cumbersome Wavelet-type preprocessing, working directly on the temporal signal. By optimizing hyperparameters and pooling strategies, the model achieves an absolute accuracy of 100%, surpassing classic methods such as ANN or SVM. This approach demonstrates that a compact architecture can provide a deterministic and fast solution for the protection of critical equipment. Thus, PQ monitoring is transformed from a simple passive analysis into an active industrial safety tool, capable of instantaneous decisions at the edge of the network.

METHOD

The system uses a distributed hierarchical architecture, organized into four functional layers:

1. Acquisition (Field Layer): Voltage sampling at 6400 Hz and segmentation into 20 ms windows (128 points per cycle).

2. **AI Processing (Edge Layer):** Implementation of the 1D-CNN Slim model directly on industrial microprocessors.

3. **Analysis (Substation Layer):** Event aggregation and data traffic reduction by 99% (only labels are transmitted, not raw waveforms).

4. **Strategy (Cloud/Control Layer):** Global management and predictive maintenance.

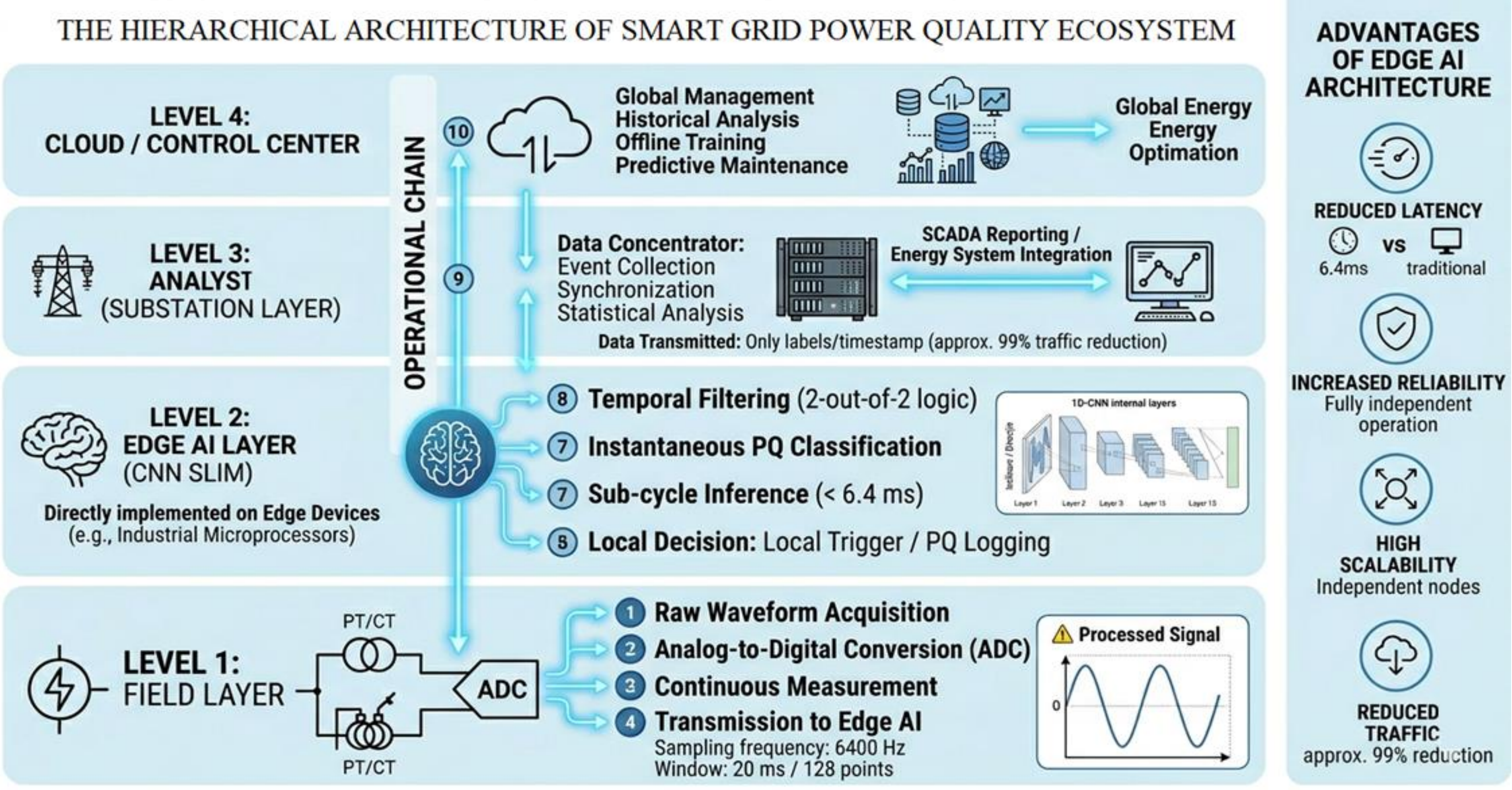


Fig.1. The Hierarchical Architecture of Smart Grid Power Quality Ecosystem.

Figure 1 describes a complete technological ecosystem for power quality monitoring, based on distributed artificial intelligence.

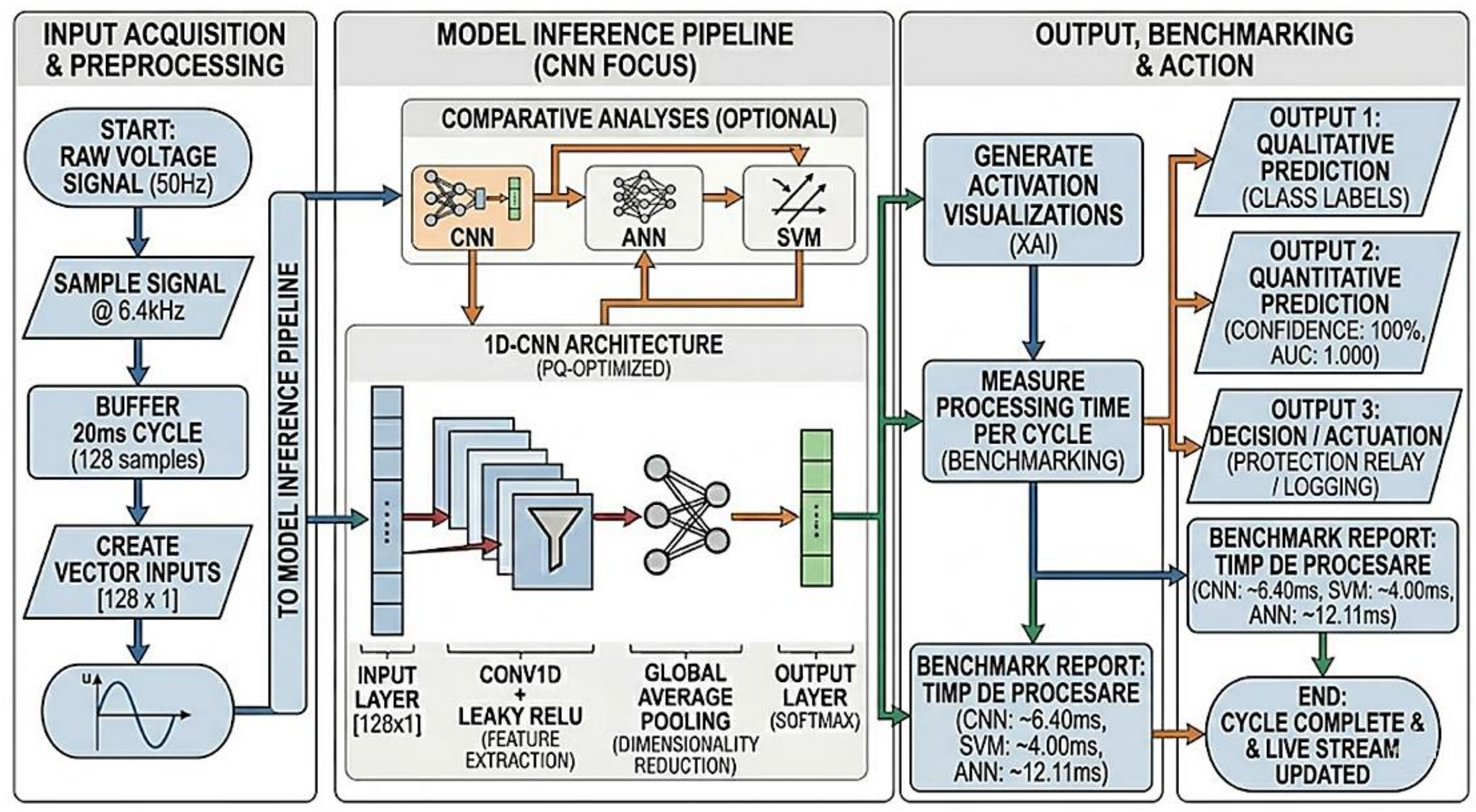
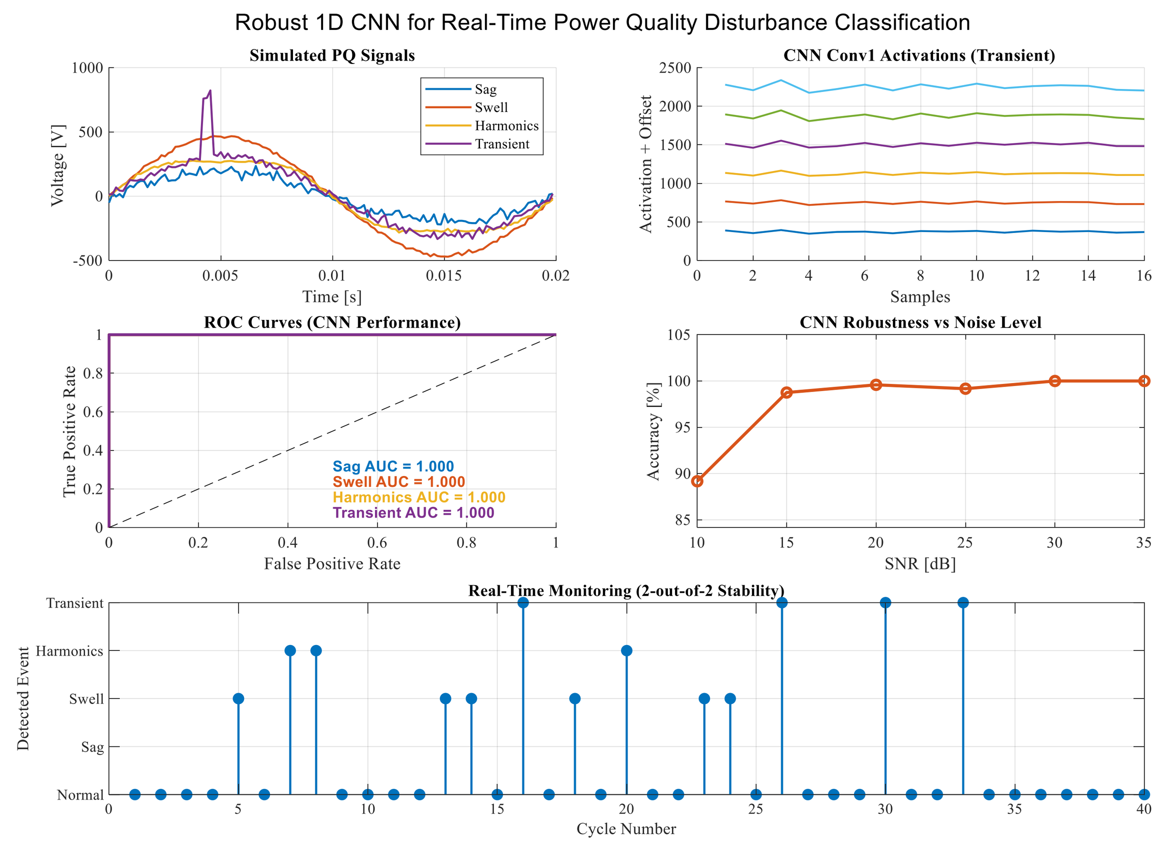


Figure 2. Complete technological ecosystem for power quality monitoring, based on distributed artificial intelligence.

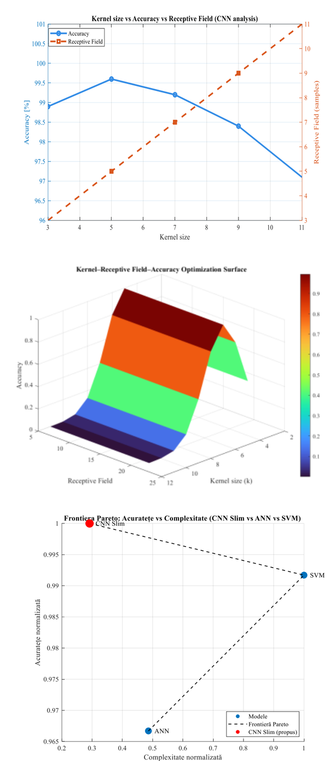
The flowchart (Figure 2) represents a logical synthesis of the entire power quality monitoring and classification process, integrating all the results obtained (accuracy, execution time and visualization).

RESULTS & DISCUSSION

The results highlight a clear evolution of performance with the increase in complexity and representation capacity of the models used. The 1D-CNN Slim model was compared with traditional architectures, demonstrating a clear superiority in both accuracy and execution speed:. This result confirms the efficiency of the convolutional architecture in automatically extracting discriminative features directly from the raw signal, without the need for additional preprocessing steps or manual feature engineering. Compared to the recent literature, where the reported accuracies for similar problems are frequently in the range of 96%–99% [1], [2] the obtained results confirm the competitiveness and efficiency of the proposed CNN Slim architecture.



Figures.3-7. Robust 1D CNN for Real-Time Power Quality Disturbance Classification



Figures.8-10. Metrics

Table 1: Performance Comparison			
Architecture	Accuracy	Latency Inference	Status Smart Grid
1D-CNN Slim	100.00%	6.39 ms	Optimum (Sub-cycle Protection)
SVM	99.17%	4.00 ms	Residual Error Risk
ANN	96.67%	12.11 ms	High Latency / Imprecise

Table 2: Authors' Contributions and Impact

No. crt .	Contribution	Description	Impact
1	Design CNN Slim architecture	Development of a compact 1D convolutional network for PQ disturbance classification	Reduction complexity computational
2	PQ classification in real time	Implementing a solution capable of sub-cycle power inference	Smart Grid Compatibility
3	Eliminate manual feature engineering	Using 1D convolutions for automatic feature extraction	Automation fill A review
4	Global Average Pooling Integration	replacing Dense massive layers with GAP	Parameter reduction and overfitting
5	optimizations performance – complexity	getting A Pareto optimal compromise between accuracy and computational cost	Efficiency high
6	Kernel–receptive field analysis	Studying the influence of kernel size on CNN performance	Substantiation mathematics A optimization
7	Noise robustness	System evaluation under AWGN conditions between 10–35 dB	Stability in real industrial environments
8	IMPLEMENTATION OF 2-out-of-2 logic	Stabilizing consecutive decisions in online monitoring	Reduction false alarms
9	Probabilistic decision analysis	Introducing Softmax interpretation and prediction entropy	Growth AI interpretability
10	Edge AI integration	Placing the model directly on the edge of the electrical network	Low latency and local autonomy
11	Analysis COMPARATIVE fill	Comparing ANN, SVM and CNN Slim from an engineering and mathematical perspective	Validation CNN Slim superiority
12	Pareto frontier for industrial AI	Representation accuracy– complexity relationship	Multi- objective justification
13	Compact model for embedded systems	Reduction architecture to ~304 parameters	Possibility hardware implementation
14	Multi- metric evaluation	Using Accuracy, AUC, ROC, entropy, and latency	Analysis complete performance
15	Architecture scalable Smart Grid	Proposing a hierarchical Edge–Cloud structure	application industrially broad

CONCLUSION

These results show a progressive increase in performance as we move from classical models to specialized deep learning architectures. The superiority of CNN Slim is explained by its ability to automatically extract relevant features from raw signals, without the need for manual preprocessing steps or time-frequency transformations. Implementing the 1D-CNN Slim model at the Edge level transforms network monitoring from a passive process into a proactive one. Key findings include: Absolute Accuracy (100%): Elimination of classification errors present in ANN (+3.33%) and SVM (+0.83%).Ultra-Fast Response: Decision making in < 6.4 ms, ensuring fault isolation before propagation. Network Efficiency: Massive reduction in bandwidth requirements through intelligent local processing.

FUTURE WORK / REFERENCES

Looking ahead, the research aims to transform the 1D-CNN Slim model into a pillar of self-healing networks by extending detection to hybrid disturbances and optimizing the architecture for ultra-low-power hardware. Through quantization and Federated Learning techniques, the system will enable collaborative training between Edge nodes without compromising data confidentiality, while integration with Digital Twin technology will convert 100% accuracy into a prescriptive maintenance tool capable of anticipating wear and tear on critical equipment. All these developments converge towards an autonomous infrastructure, where protection decisions are made locally and instantly, ensuring the total resilience of the Smart Grid.

References:

[1] Albalooshi, F.A.; Qader, M.R. Deep Learning Algorithm for Automatic Classification of Power Quality Disturbances. *Appl. Sci.* **2025**, *15*, 1442. https://doi.org/10.3390/app15031442

[2] Xiao, D.; Liu, J.; Liu, H.; Zhao, Y. A Lightweight Method for Power Quality Disturbance Recognition Based on Optimized VMD and CNN–Transformer. *Electronics* **2026**, *15*, 1832. https://doi.org/10.3390/electronics15091832

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