



Title: Power Grid Anomaly Detection and Prediction of Physical and Cyber Attacks

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Introduction

Smart grids integrate power systems with digital communication, sensors, and automation to enable efficient and reliable energy management. However, this increased connectivity exposes the grid to cyber-attacks and physical anomalies that are difficult to detect using traditional rule-based monitoring systems. Conventional threshold-based techniques fail to capture the temporal and multivariate behavior of smart grid data. This project proposes an AI-based cyber-physical anomaly detection framework that leverages machine learning and deep learning models to detect abnormal behavior in both physical power systems and cyber communication networks.

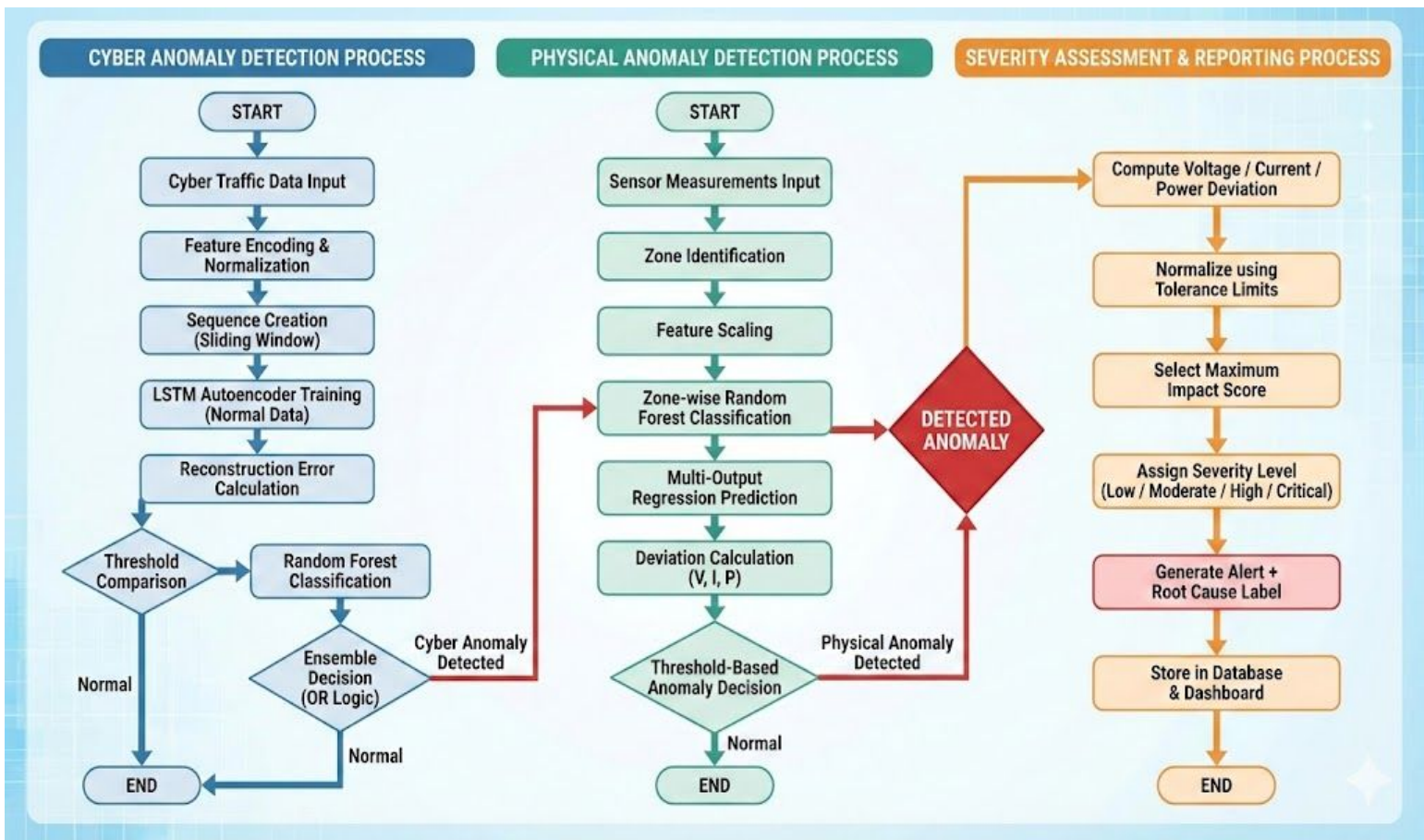
Problem Definition

Current monitoring systems struggle to reliably distinguish normal operational variations from malicious or faulty behavior in time-series cyber and power grid data, resulting in false alarms and missed anomalies.

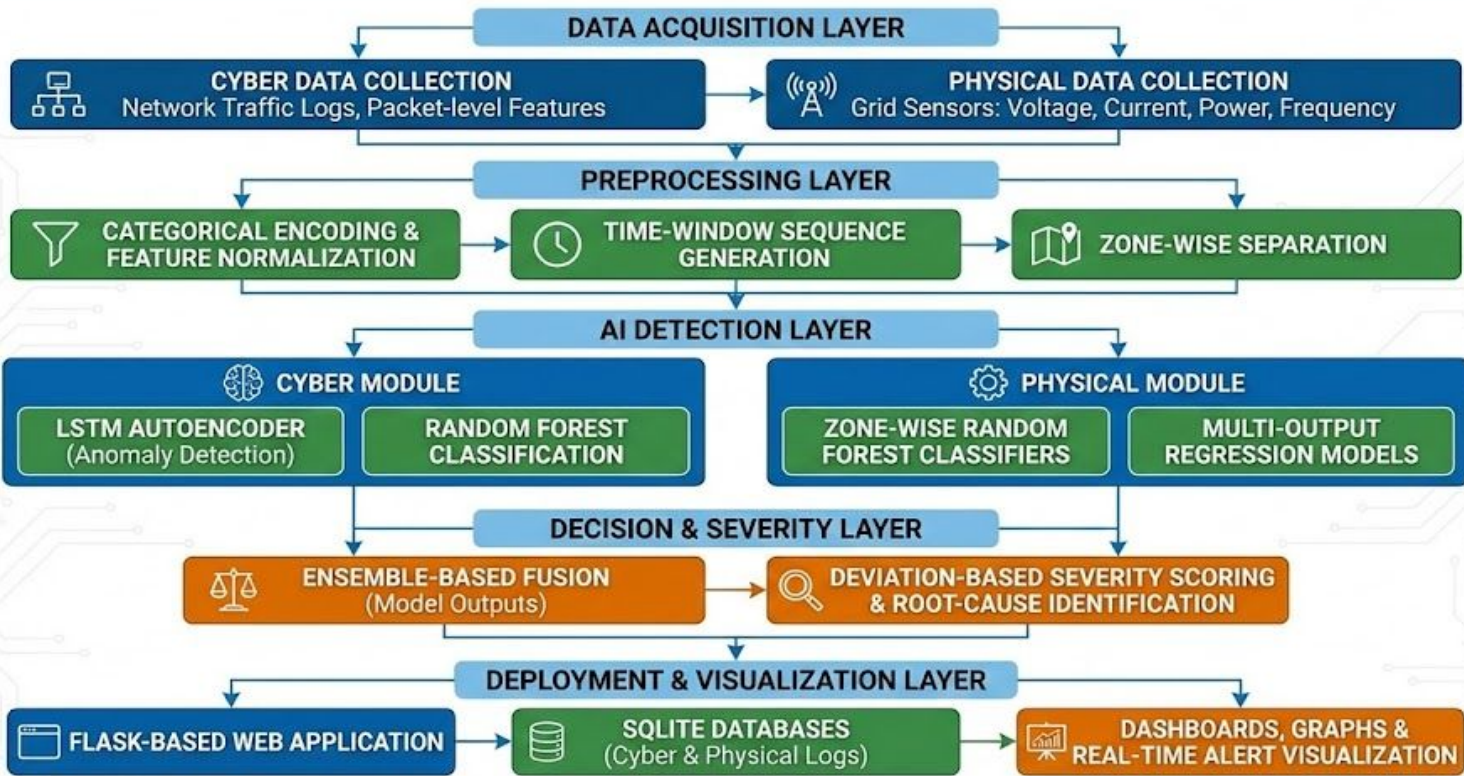
Objectives

- To detect cyber-attacks and physical anomalies in smart grid environments using AI techniques
- To model normal system behavior using time-series learning
- To improve detection accuracy through ensemble learning
- To provide interpretable and reliable anomaly detection
- To enable real-time monitoring and visualization of anomalies

Methodology



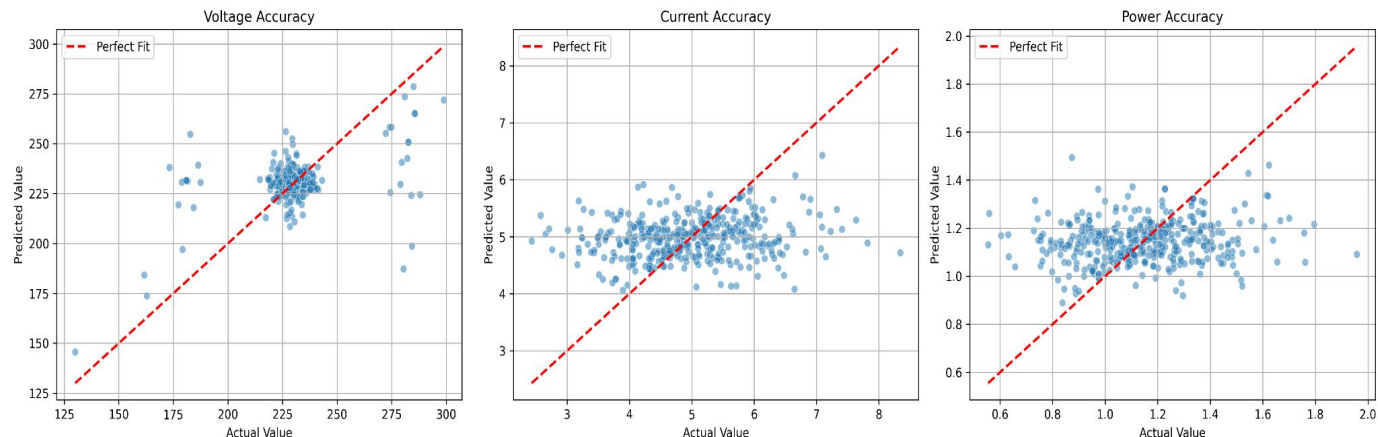
CYBER-PHYSICAL SYSTEM AI ARCHITECTURE DIAGRAM



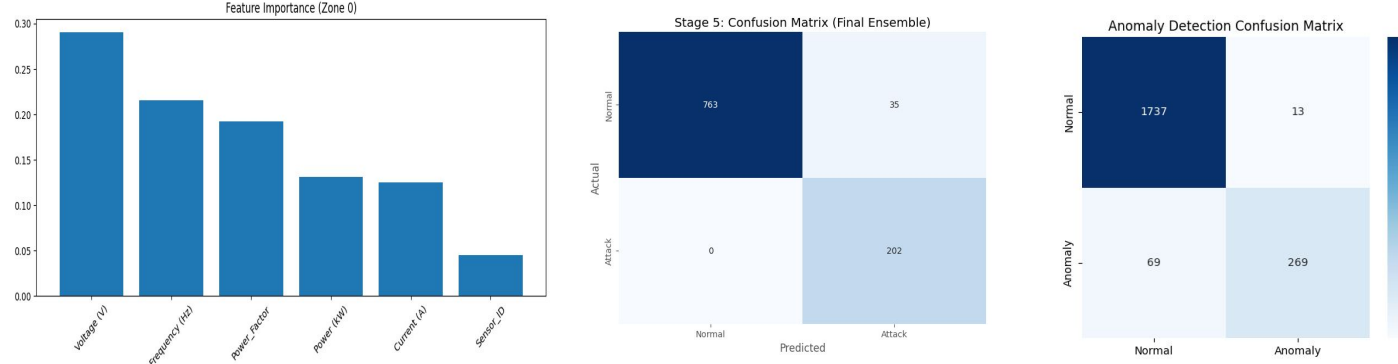
Tools used

- Programming Language: Python
- Deep Learning: LSTM Autoencoder
- Machine Learning: Random Forest Classifier
- Libraries: NumPy, Pandas, Scikit-learn, TensorFlow/Keras, Matplotlib, Seaborn
- Web Framework: Flask
- Database: SQLite
- Visualization: Confusion matrices, feature importance plots, time-series graphs

Results and Discussions



The proposed framework effectively detects both cyber-attacks and physical anomalies with high accuracy and low false alarm rates. The LSTM autoencoder successfully learns normal temporal behavior and identifies anomalies using reconstruction error.



Conclusions

This project presents an AI-based cyber-physical anomaly detection framework for smart grids that combines deep learning and ensemble machine learning models. By integrating temporal modeling, feature-based classification, and zone-wise analysis, the system overcomes the limitations of traditional monitoring methods. The results demonstrate improved detection accuracy, interpretability, and practical applicability, making the framework suitable for real-world smart grid security and monitoring applications.

References

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