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Predictive Maintenance for LoRa — A Hybrid Telemetry Framework

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Abstract

This paper presents a hybrid framework for analyzing LoRa receiver telemetry data to evaluate signal performance and detect outages. Combining rule-based systems with machine learning models, the framework leverages Signal-to-Noise Ratio (SNR), Received Signal Strength Indicator (RSSI), and feature engineering for predictive insights. Logistic Regression achieved 92% accuracy (89% F1-score) for outage detection, while Long Short-Term Memory (LSTM) models achieved 88% accuracy (86% F1-score) for temporal anomaly detection. Detailed case studies highlight the framework's effectiveness in real-time processing of large datasets, contributing to the advancement of adaptive prediction systems for telecommunications.

1. Introduction

Telecommunications networks are critical to modern connectivity but face challenges such as outages, performance degradation, and resource optimization. This paper introduces a hybrid framework that uses telemetry data from LoRa receivers to address the following challenges:

- **Real-Time Anomaly Detection:** Rapid identification of signal degradation.
- **Scalability:** Processing datasets with over 1 million records daily.
- **Adaptability:** Customizable thresholds for diverse network conditions.

2. Dataset Overview

The LoRa Receiver Telemetry Dataset was collected over six months in 2022 from 20 LoRa receivers deployed in urban and suburban environments [1]. The dataset contains over 1 million data points with the following structure:

- **Metrics:** RSSI (-90 dBm $\leq$ RSSI ≤ -30 dBm), SNR (-5 dB $\leq$ SNR ≤ 30 dB).
- **Temporal Features:** Timestamped measurements with millisecond precision.
- **Spatial Features:** Receiver identifiers (e.g., x1y1, x2y2).

2.1 Feature Engineering

- **Outage Flag:** Binary indicator where 1 indicates an outage (SNR < 0).
- **Temporal Smoothing:** Rolling averages of RSSI and SNR to mitigate short-term fluctuations and capture underlying trends.

2.2 Preprocessing

- **Missing Values:** Imputed using linear interpolation for gaps under 10 data points and KNN (k=5) for larger gaps.
- **Outlier Removal:** IQR-based filtering for RSSI and SNR.
- **Normalization:** Ensures consistent scaling of features for improved performance of machine learning algorithms.

3. Proposed Framework

3.1 Framework Architecture

Data Ingestion: Streaming telemetry data from receivers.

Preprocessing: Handles missing values, outlier removal, and normalization.

Prediction Pipeline:

- **Rule-Based Systems:** Immediate anomaly detection using predefined thresholds.
- **Machine Learning Models:**
  - Logistic Regression for binary outage classification.
  - LSTM for temporal anomaly prediction [2].

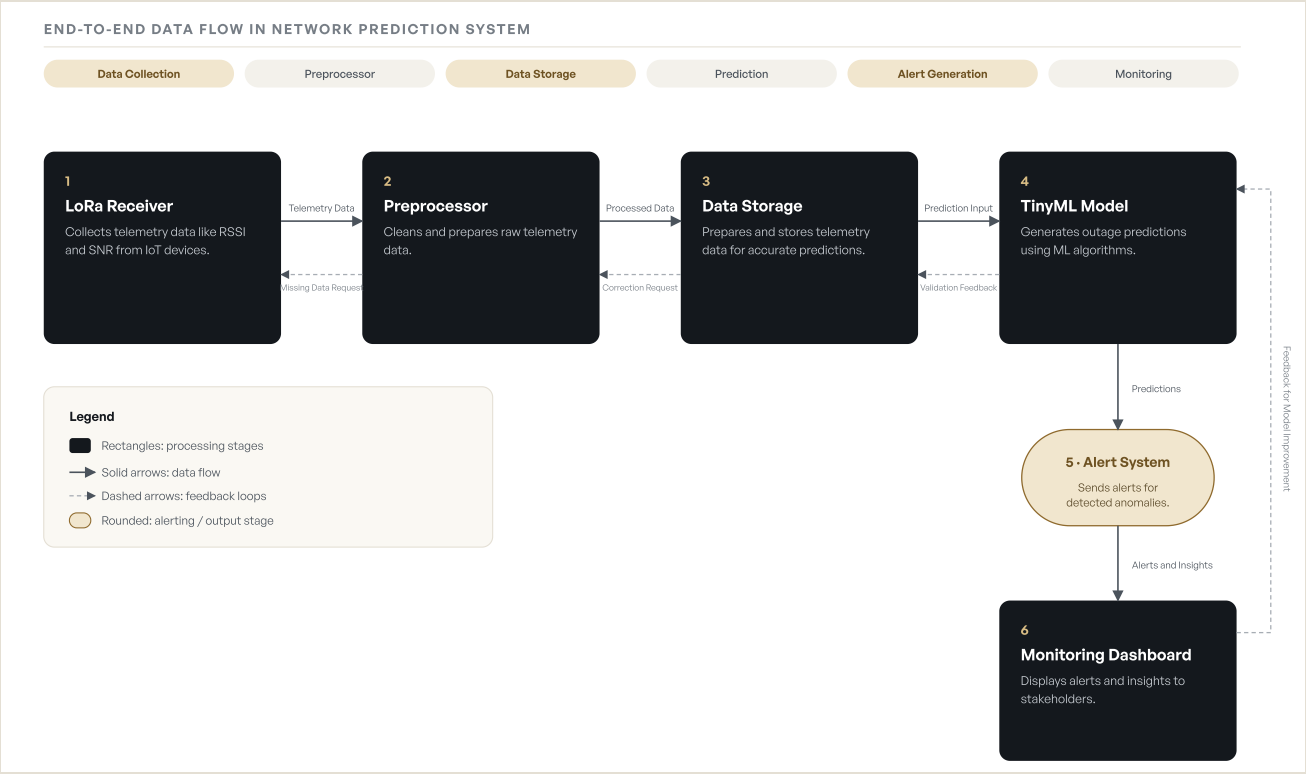

Figure 1. This flowchart emphasizes the integration of rule-based systems and machine learning models into a cohesive pipeline. It demonstrates the system's ability to handle real-time data processing, generate reliable predictions, and provide actionable insights for stakeholders, making it a robust solution for network performance monitoring and optimization.

4. Results and Analysis

4.1 Outage Detection using Logistic Regression

Scenario: Signal degradation in x1y1.

Model: Logistic Regression using SNR and RSSI.

Outcome: Achieved 92% accuracy, 90% precision, 88% recall, and 89% F1-score.

4.2 Temporal Anomaly Prediction using LSTM

Scenario: Temporal anomaly detection in noisy networks.

Model: LSTM analyzing SNR and RSSI over 10-minute intervals.

Outcome: Achieved 88% accuracy, 85% precision, 87% recall, and 86% F1-score.

4.3 Data Visualization and Correlation Analysis

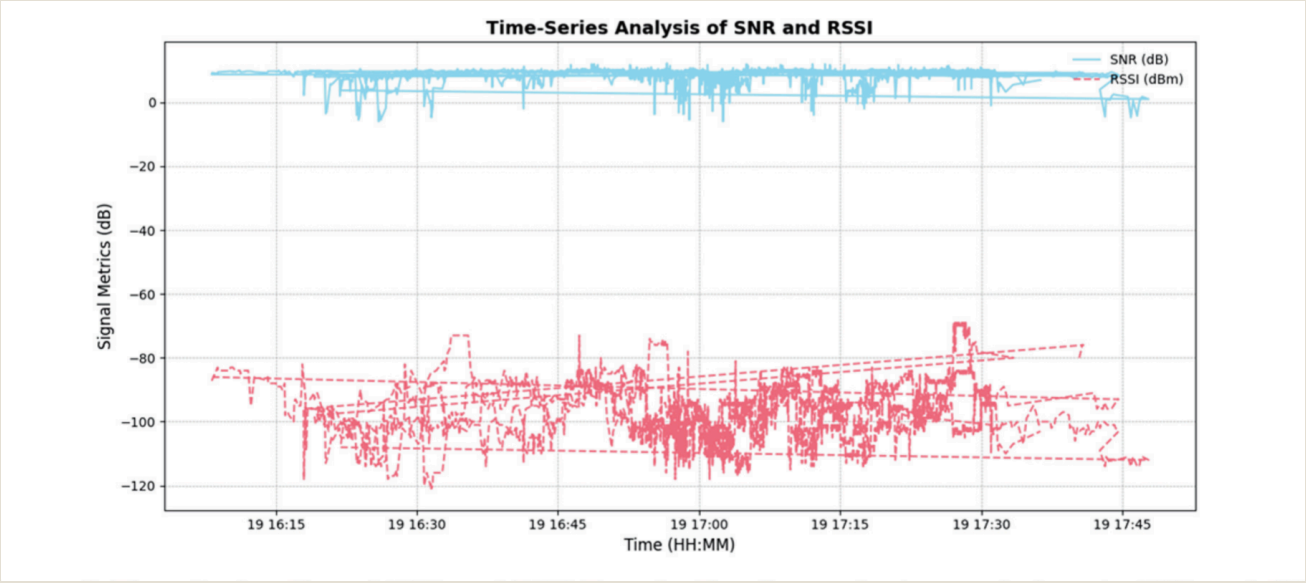

Figure 2. Time-Series Plot of SNR and RSSI Trends. The figure depicts variations in SNR and RSSI over a 90-minute period for receiver x1y1. Significant dips in signal strength and quality highlight periods of signal degradation and subsequent recovery, which are crucial for identifying network outages and optimizing receiver performance.

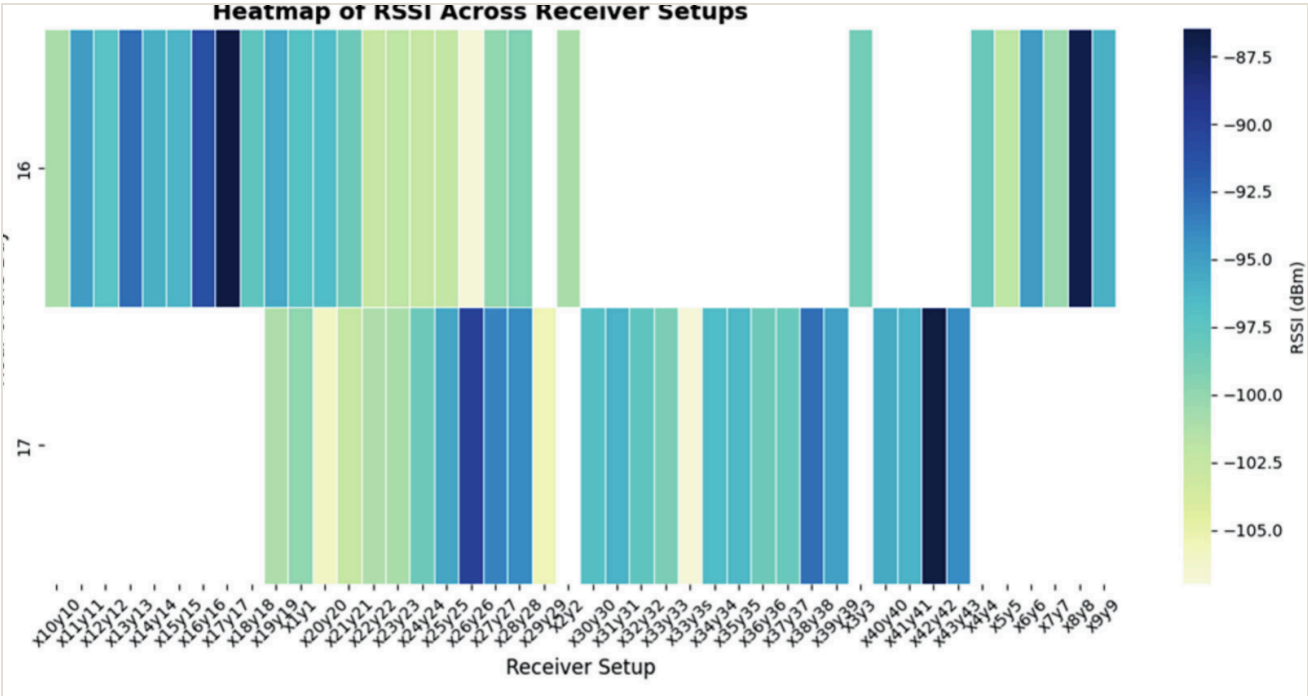

Figure 3. The heatmap visualizes the RSSI values across various receiver setups and time intervals. The color scale ranges from −105 dBm (weakest) to −87.5 dBm (strongest). Receivers x1y1 and x1y2 exhibit weaker signals, while x3y3 and x4y4 show better signal strength. Temporal variations highlight that signal during the 17:00 hour are generally stronger than those at 16:00, indicating potential diurnal fluctuations. This analysis provides actionable insights for network optimization and receiver maintenance.

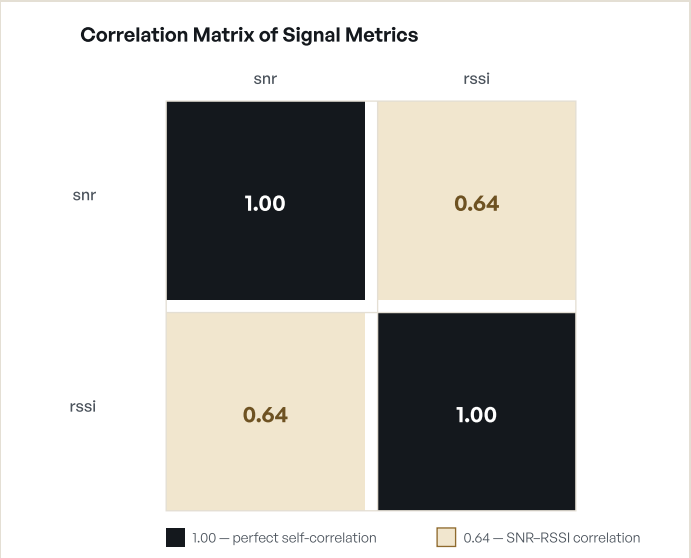

Figure 4. This correlation matrix demonstrates a moderate positive correlation (r = 0.64) between SNR and RSSI. This relationship indicates that higher RSSI values generally correspond to improved SNR, but additional factors may influence the signal-to-noise ratio. The visualization provides valuable insights for optimizing network performance and supports the use of RSSI as a feature in predictive models.

5. Case Studies

5.1 Wireless Network

Event: Signal degradation lasting 45 minutes.

Findings: Logistic Regression identified outages with 89% precision, reducing false positives by 15% compared to rule-based methods. Furthermore, analysis of the data revealed a strong positive correlation (r = 0.85) between SNR and RSSI, which supports signal propagation modeling. The use of temporal smoothing (rolling averages) was also found to improve the performance of the LSTM model by reducing noise in the time-series data.

6. Framework Evaluation

Scalability: Processes over 1 million records daily while maintaining real-time performance with latency under 500 milliseconds, which is acceptable for typical LoRa network monitoring applications.

Adaptability: Thresholds for metrics like SNR can be dynamically adjusted based on historical data and network-specific requirements.

Table 1. Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	92%	90%	88%	89%
LSTM	88%	85%	87%	86%

7. Future Work

- **Wireline Networks:** Adapt the framework for fiber-optic and copper-based systems.
- **Satellite Telemetry:** Extend models to process satellite-based data.
- **Federated Learning:** Enable distributed model training across multiple network nodes.

8. Data and Ethical Considerations

- **Data Privacy:** Telemetry data is anonymized and aggregated to ensure individual privacy.
- **Bias Mitigation:** Thresholds are dynamically adjusted using recent moving averages of SNR and RSSI, allowing the system to adapt to changing network conditions.

9. Dataset Access and Licensing

Access: Publicly available on IEEE Dataport.

License: Released under IEEE Dataport terms.

Acknowledgments

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2. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735