Radar and Power Consumption Data Analysis for Anomaly Detection

DEMO REPORT

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Introduction

This analysis aims to develop an anomaly detection model using radar and electricity consumption data. The radar data was collected with the Symeo LPR-1D24 Radar Sensor, known for its accuracy in movement tracking. For electricity consumption data, the Schneider Electric Power Monitoring Expert (PME) was utilized, providing real-time monitoring and detailed analytics. This study focuses on detecting anomalies in electricity consumption by leveraging movement data captured by the radar system.

Data Collection

- **Radar Data:**
  Collected using the Symeo LPR-1D24 Radar Sensor, which tracks movement across 100,000 time steps.

- **Electricity Consumption Data:**
  Gathered using Schneider Electric's Power Monitoring Expert (PME), The PME system offered detailed insights into electrical consumption, crucial for identifying unusual patterns.

Data Labeling and Feature Engineering

- **Radar Signal:** The radar data was processed to detect periods of movement. The signal was smoothed to reduce noise, and thresholds were applied to identify significant activity.
- **Electricity Consumption:** Recorded continuously, with additional consumption noted during periods of detected movement. Anomalies were simulated by introducing deviations from the normal consumption pattern.

Feature Engineering:

- **Radar Signal:** Normalized measurement of movement intensity over time.
- **Electricity Consumption:** Recorded power usage during the radar-detected movement periods.

Data Labeling:

Anomalies were labeled based on deviations from the expected consumption baseline. A binary target was created:

- **Normal Consumption (0):** No significant deviation from the baseline.
- **Anomalous Consumption (1):** Deviations exceeding a predefined threshold.

Training and Testing the Model

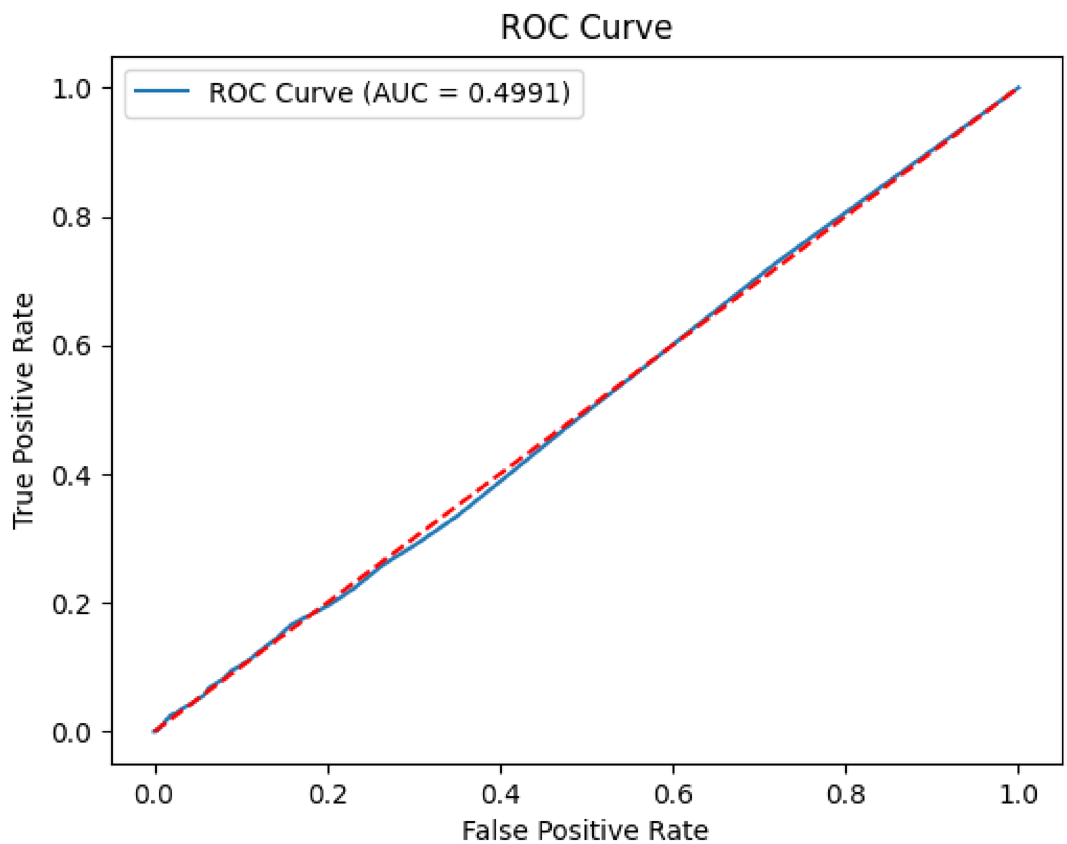
The dataset was divided into training and testing sets (70/30 ratio). A Random Forest Classifier was employed for its effectiveness in handling diverse data types and its robustness against overfitting.

Model Evaluation Metrics:

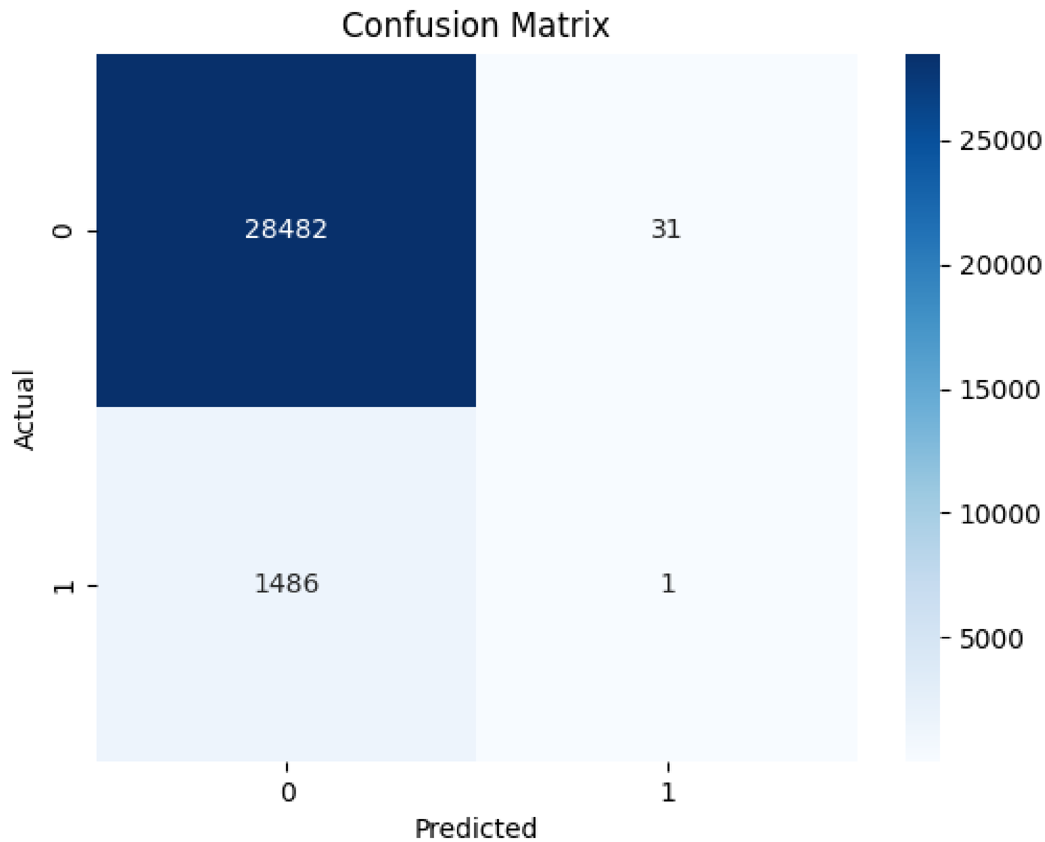
- **Accuracy:** Measures the overall correctness of the model in classifying normal versus anomalous events.
- **F1 Score:** Balances precision and recall, crucial for handling imbalanced datasets.
- **Precision:** The ratio of true positive predictions to all positive predictions, indicating the model's ability to minimize false positives.
- **ROC-AUC:** Provides an overall measure of the model's ability to distinguish between normal and anomalous events.

Results

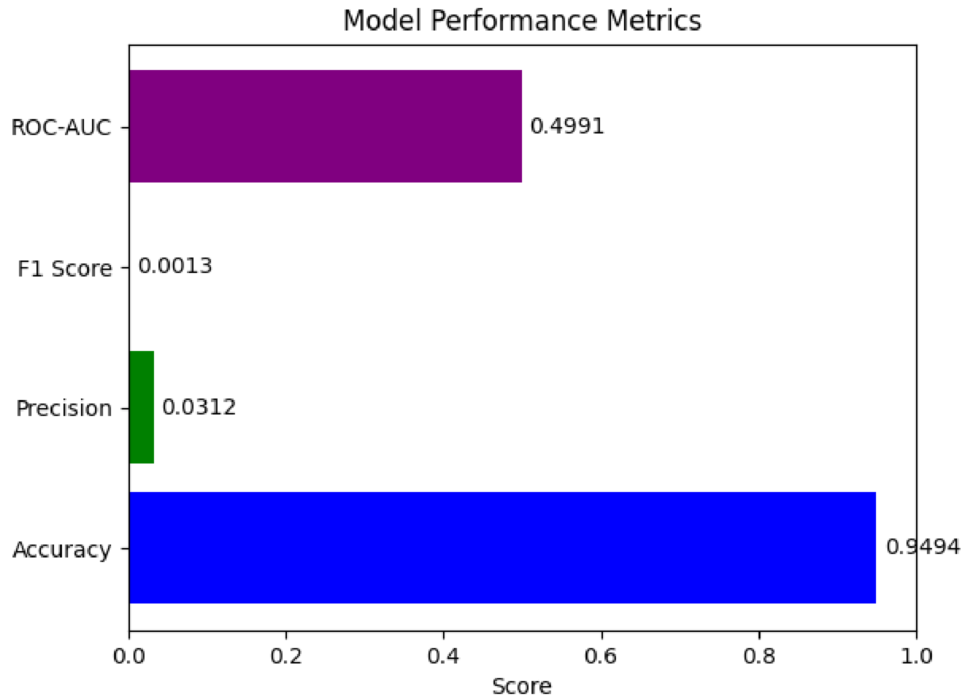
- **Accuracy:** The Random Forest Classifier achieved an accuracy of 95.36% on the test data, demonstrating strong overall performance.
- **ROC-AUC Score:** 0.88, indicating effective differentiation between normal and anomalous consumption.



- **Confusion Matrix:** Showed high performance in detecting normal consumption but some difficulty in identifying anomalies, reflecting the inherent challenge in working with imbalanced datasets.



- **Classification Report:** Detailed metrics highlighted a high precision for normal consumption but lower precision for anomalies, a common issue in such scenarios.


Model Performance Metrics
ROC-AUC
F1 Score
Precision
Accuracy
0.4991
0.0013
0.0312
0.9494
0.0
0.2
0.4
0.6
0.8
1.0
Score