The Abdus Salam International Centre for Theoretical Physics

PDM

R-PODID

AI Model for Motor Health Prediction and Network Anomaly Detection

Predictive Industrial Motor Maintenance

Gateway network anomaly detection

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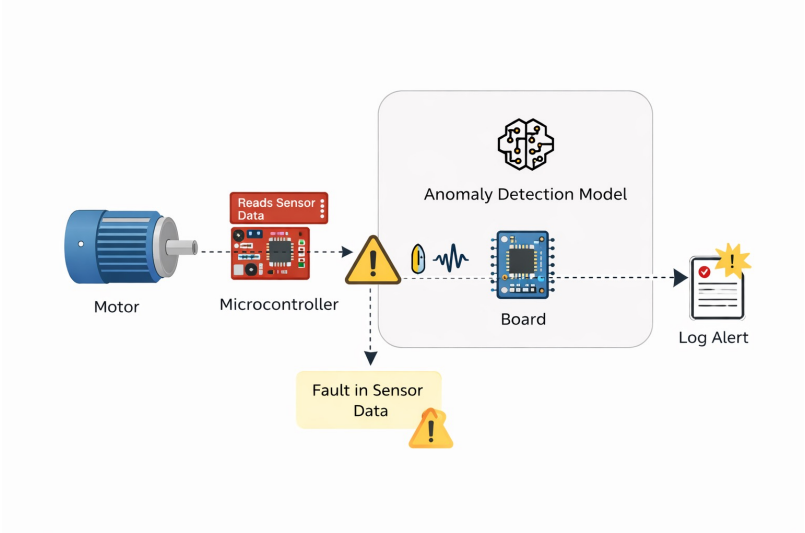
School on Applied AI for Sustainable Development

What Are We building

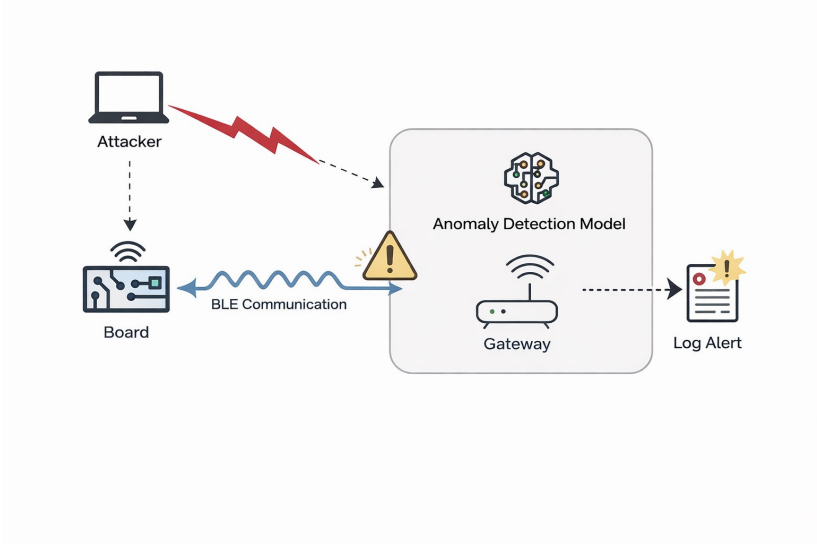
Task 1 - Predictive Industrial Motor Maintenance

- Board AI reads motor sensor streams in real time.
- Goal: Detect faults before failure or severe degradation.
- Key Cues: Temperature raising, high vibration, higher current values



Task 2 - Gateway Network Anomaly Detection

- AI learns what normal gateway traffic looks like.
- Goal: Flag unusual behavior that may indicate attack.
- Key cues: Increase of packet sizes, packet rates from board higher then normal.



Task 1 · Predictive Industrial Motor Maintenance

Model core

- LSTM learns normal temporal patterns from multiple sensors values.
- DNN turns those temporal features into a health score.
- Training data combines normal behavior with added faults.

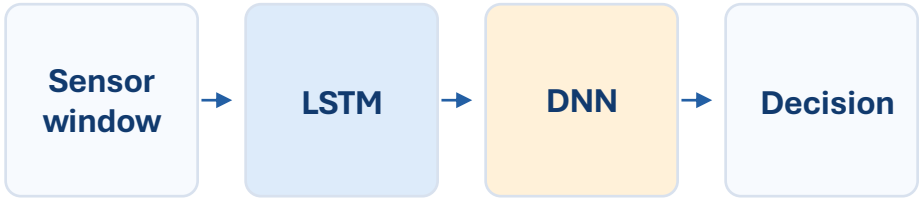
Inputs

- Vibration
- Temperature
- Current / power
- RPM or speed
- Trend windows

Faults added

- Bearing wear
- Rotor imbalance
- Overheating
- Sudden load change
- Supply instability

System view



Possible health states

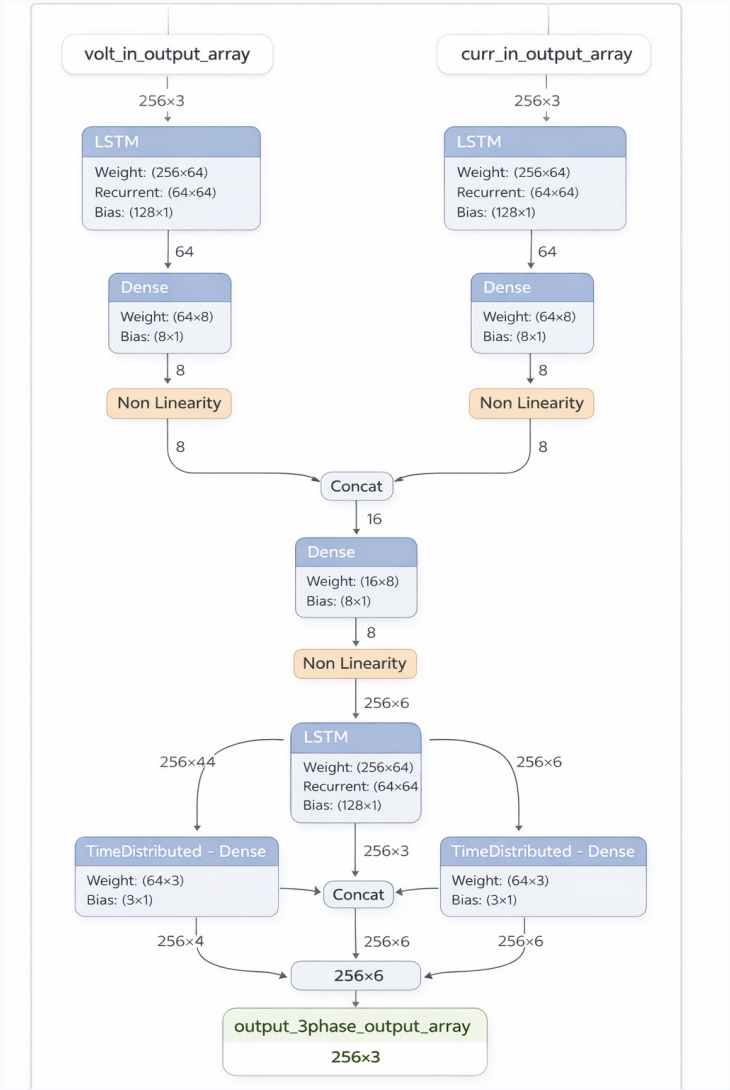
LSTM+DNN: Features Visualization

Operating State	Time Step	Motor Temp (°C)	Bearing Temp (°C)	Vibration RMS (mm/s)	Current (A)	RPM	Anomaly Score
Normal	t-9	61.8	58.9	1.7	12.4	1498	0.05
Normal	t-8	62.0	59.1	1.8	12.5	1500	0.06
Normal	t-7	62.3	59.4	1.8	12.5	1499	0.07
Normal	t-6	62.7	59.8	1.9	12.6	1498	0.08
Normal	t-5	63.1	60.2	1.9	12.7	1497	0.10
Normal	t-4	65.8	62.6	2.0	13.0	1496	0.22
Normal	t-3	69.2	65.7	2.2	13.4	1494	0.41
Early overheating	t-4	65.8	62.6	2.2	13.4	1496	0.22
Early overheating	t-3	69.2	65.7	2.2	13.4	1494	0.41
Overheating	t-2	74.6	70.6	2.5	14.0	1492	0.68
Overheating	t-1	81.7	77.4	2.9	14.8	1489	0.93

For an overheating case:

- Motor and bearing temperatures rise.
- Current also increases because the motor is working harder.
- RPM drops slightly under stress.
- Vibration may increase a bit.

LSTM+DNN Architecture



Inputs

- Voltage and current are processed in parallel sequence branches.
- Each input is a time window with three signal channels.

Model flow

- LSTM layers learn temporal patterns and signal evolution.
- Dense + nonlinearity blocks compress and refine each branch.
- Concatenation fuses both branches before the final predictor.

Output

- TimeDistributed Dense layers generate the 3-phase output sequence.

Why this model

- LSTM has internal memory and learns how each sensor is supposed to behave in a healthy state.
- DNN refines those temporal features to generate the final 3-phase output (U, V, W).

Task 2 · Gateway Network Anomaly Detection

Model core

- Isolation Forest works well when suspicious behavior is rare.
- Training does not require every attack to be labeled.
- Model was trained with synthetic BLE traffic with normal communication and injected attacks.

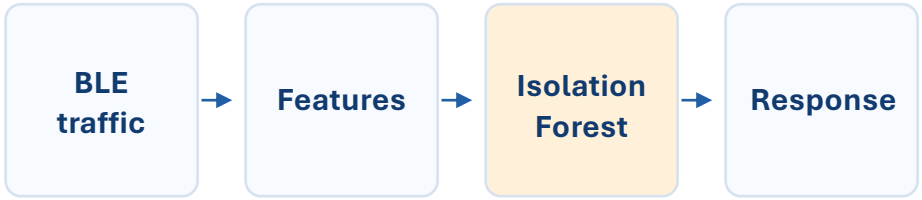
Features

- Packets per window
- Packet size
- Inter-arrival time
- Node behavior
- Sequence irregularity

Attacks added

- Packet flooding / DDoS
- Replay attack
- Spoofed device
- Malformed payload
- Burst connect requests

System view



Typical responses

Log event | Raise alert | Inspect node

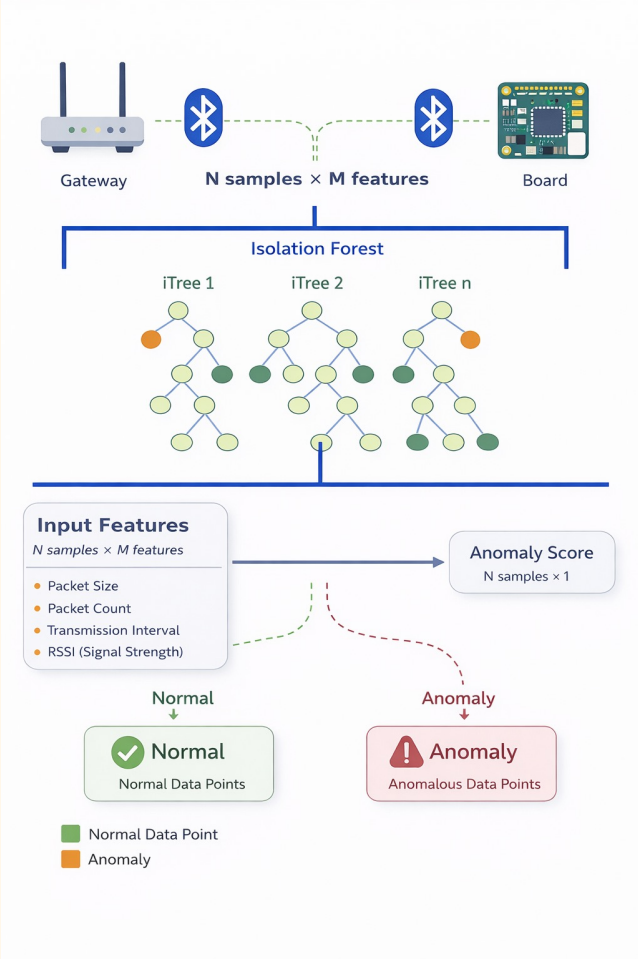
Isolation Forest: Features Visualization

Communication State	Timestamp	Packets in 5 s	Mean Inter-arrival (ms)	Retransmis	CRC Errors	Avg Payload (B)	RSSI Std Dev (dBm)	Isolation Score
Normal	10:21:00	18	278	0	0	24	1.1	0.07
Normal	10:21:05	19	263	0	0	24	1.0	0.08
Normal	10:21:10	18	279	1	0	24	1.2	0.08
Normal	10:21:15	20	251	0	0	24	1.1	0.09
Normal	10:21:20	19	264	0	0	24	1.2	0.11
Normal	10:21:25	42	119	2	0	24	1.2	0.07
Suspicious	10:21:30	42	119	4	1	24	1.2	0.24
Suspicious	10:21:35	76	66	4	1	24	2.2	0.24
Suspicious	10:21:30	128	39	9	2	24	2.2	0.28
Anomalous	10:21:35	181	28	15	4	25	2.9	0.72
Anomalous	10:21:40	181	28	15	4	25	2.9	0.91

For a BLE flood case:

- Packet count rises sharply within the communication window.
- Mean inter-arrival time decreases as packets arrive more frequently.
- Retransmissions increase due to channel congestion.
- CRC errors may rise slightly under stressed communication.

Isolation Forest Architecture



Input features

- BLE traffic is converted into feature vectors for each communication sample/window.
- Example features include packet size, packet count, transmission interval, and RSSI.

Model flow

- Isolation Forest builds many random isolation trees (iTrees).
- Each iTree randomly selects a feature and a split value.
- Rare communication patterns are isolated in fewer splits.

Output

- The forest combines path lengths into an anomaly score.
- The forest combines path lengths into an anomaly score.

Why this model

- Isolation Forest is an unsupervised model and learns what normal BLE behavior looks like.
- Good for zero day attacks that cant be labeled.

One Project, Two Applications

Motor maintenance

Observed system	Industrial motor
Main data	Sensor time series
Model	LSTM + DNN
Anomalies	Wear, heat, imbalance
Value	Service before failure

Gateway cybersecurity

Observed system	BLE gateway traffic
Main data	Packet statistics features
Model	Isolation Forest
Anomalies	Spoofing, replay, bursts
Value	Alert and inspect

Thank you