

SCHOOL OF BUSINESS, ADMINISTRATION AND
ECONOMICS

Unsupervised Anomaly Detection in Industrial IoT Streams
using LSTM-Autoencoders and Heuristic Decision Strategies

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**Diploma Thesis submitted for Bachelor of Science in Applied
Computer Science at Neapolis University Paphos**

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Midum Dew Sahan Thuram

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TABLE OF CONTENTS

1. INTRODUCTION

- 1.1 Research Problem
- 1.2 Problem Statement
- 1.3 Research Aim and Objectives
- 1.4 Research Questions
- 1.5 Scope and Limitations
- 1.6 Structure of the Dissertation

2. THEORETICAL FOUNDATION AND LITERATURE REVIEW

- 2.1 Internet of Things (IoT) and Industrial Monitoring

- 2.2 Machine Learning for Time-Series Analysis
 - 2.2.1 The Challenge of Class Imbalance
 - 2.2.2 Transition to Unsupervised Reconstruction Models
 - 2.2.3 Feature Engineering vs. Representation Learning
- 2.3 Deep Learning and LSTM Architectures
 - 2.3.1 Mathematical Logic of Gating Mechanisms
- 2.4 Comparative Analysis of Anomaly Detection Techniques
 - 2.4.1 Isolation Forests (IF)
 - 2.4.2 Gated Recurrent Units (GRU)
 - 2.4.3 Traditional Statistical Thresholds vs. AI

3. RESEARCH METHODOLOGY

- 3.1 Research Design
- 3.2 Data Sources and Characterization
- 3.3 Data Pre-processing and Feature Scaling
 - 3.3.1 Resampling and Normalization Pipelines
 - 3.3.2 Sliding Window Transformation
- 3.4 LSTM-Autoencoder Architecture
 - 3.4.1 Encoder-Decoder Mechanism
 - 3.4.2 Leveraging LSTM for Long-Term Memory
 - 3.4.3 The Role of the Cell State and Memory Channel
 - 3.4.4 Functional Gating for IoT Data Filtering
- 3.5 Heuristic Decision Engine
 - 3.5.1 The 6-Window Persistence Rule
 - 3.5.2 Justification for the Heuristic
- 3.6 Ethical Considerations

4. SYSTEMS ANALYSIS AND DESIGN

- 4.1 Requirements Analysis
- 4.2 Development Environment and Computing Resources
- 4.3 Data Pipeline and Integration Flow
- 4.4 Proposed LSTM-Autoencoder Architecture
- 4.5 Design of the Heuristic Decision Engine
- 4.6 Chapter Summary

5. IMPLEMENTATION AND RESULTS ANALYSIS

- 5.1 Introduction to the Experimental Setup
- 5.2 Computational Environment and Data Ingestion
- 5.3 Baseline Profiling and Temporal Partitioning
- 5.4 Feature Normalization and Sequence Windowing
- 5.5 Model Construction and Training Convergence
- 5.6 Statistical Threshold Calibration
- 5.7 Evaluation on Unseen Test Stream

5.8 Chapter Summary

6. DISCUSSION

6.1 Interpretation of Findings

6.2 Comparison with Existing Literature

6.3 Operational Trajectory Analysis

6.4 Architectural Boundaries and Constraints

6.5 Chapter Summary

7. CONCLUSIONS AND FUTURE WORK

7.1 Study Summary and Academic Contributions

7.2 Study Limitations

7.3 Recommendations for Future Research

ABSTRACT

The fast-growing IIoT infrastructure, which consists of high-frequency sensor telemetry, can be overwhelming to the point of “alert fatigue.” For example, in predictive maintenance applications, a factory’s control system can get swamped by alerts to the extent that operators start to ignore valid warnings of mechanical failures. This thesis addresses the need for anomaly detection at scale in a noise-tolerant manner for Cyber Physical Systems (CPS).

As a proposed solution, I present an unsupervised, sequence-aware monitoring framework built upon a Long Short-Term Memory (LSTM) Autoencoder. In an industrial setting, failure data is scarce which can severely limit the usability of classification-based anomaly detection approaches. The proposed LSTM Autoencoder instead learns the latent sequences of normal behavior for the given time series from unlabeled data.

To enable interpretable decision-making using the model outputs, I propose the Heuristic Decision Engine, which implements a multi-tier severity threshold along with a temporal persistence check in order to validate alerts within a given timeframe. If the anomaly score remains elevated for a minimum of 30-minutes of consecutive, 5-minute window segments, then an alert is sent.

For validation, I tested the framework on the Numenta Anomaly Benchmark dataset. Through a combination of empirical and qualitative experiments, I show that a system based on my anomaly detection framework would be robust in distinguishing between normal sensor jitter and real-time thermodynamic anomaly. By mapping 497 real-world anomalies detected with the Autoencoder framework to 34 anomalous behavior events that would be flagged as “alertworthy” by my heuristic decision engine, it would be possible to reduce alert fatigue by filtering spurious alerts while still providing high accuracy anomaly detection at scale. In summary, this study presents an unsupervised anomaly detection approach that has been proven to be viable for industrial applications in the era of big data and IoT.**Keywords:** Anomaly Detection,